Deep learning for image recognition II

Data Science Retreat Berlin | 28.02.2017

Ludwig Schmidt-Hackenberg

Quiz I

Q: What does the weights vector do?

A: It defines the importance of a neuron's inputs

Q: What does the bias do?

A: It changes the neuron's output independent of the input

Q: What is gradient descent?

A: A optimization algorithm to find a local minimum for a function

Quiz II

Q: What is the learning rate?

A: Is the step size (factor) of the gradient descent

Q: What is stochastic gradient descent?

A: Using only a random (thus stochastic) subset of the data for gradient descent

Q: What is an epoch?

A: A SGD training run using all data

Quiz III

Q: What is the cost function?

A: A function that returns a number representing how well the neural network performed mapping training examples to correct output.

Q: What is a loss function?

A: A different name for the cost function.

Q: What is regularization?

A: (Here) The process of introducing additional information into a learning process to prevent overfitting.

Quiz III

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Q: What is a loss function?

A: A different name for the cost function.

Q: What is regularization?

A: (Here) The process o
a learning process to pre

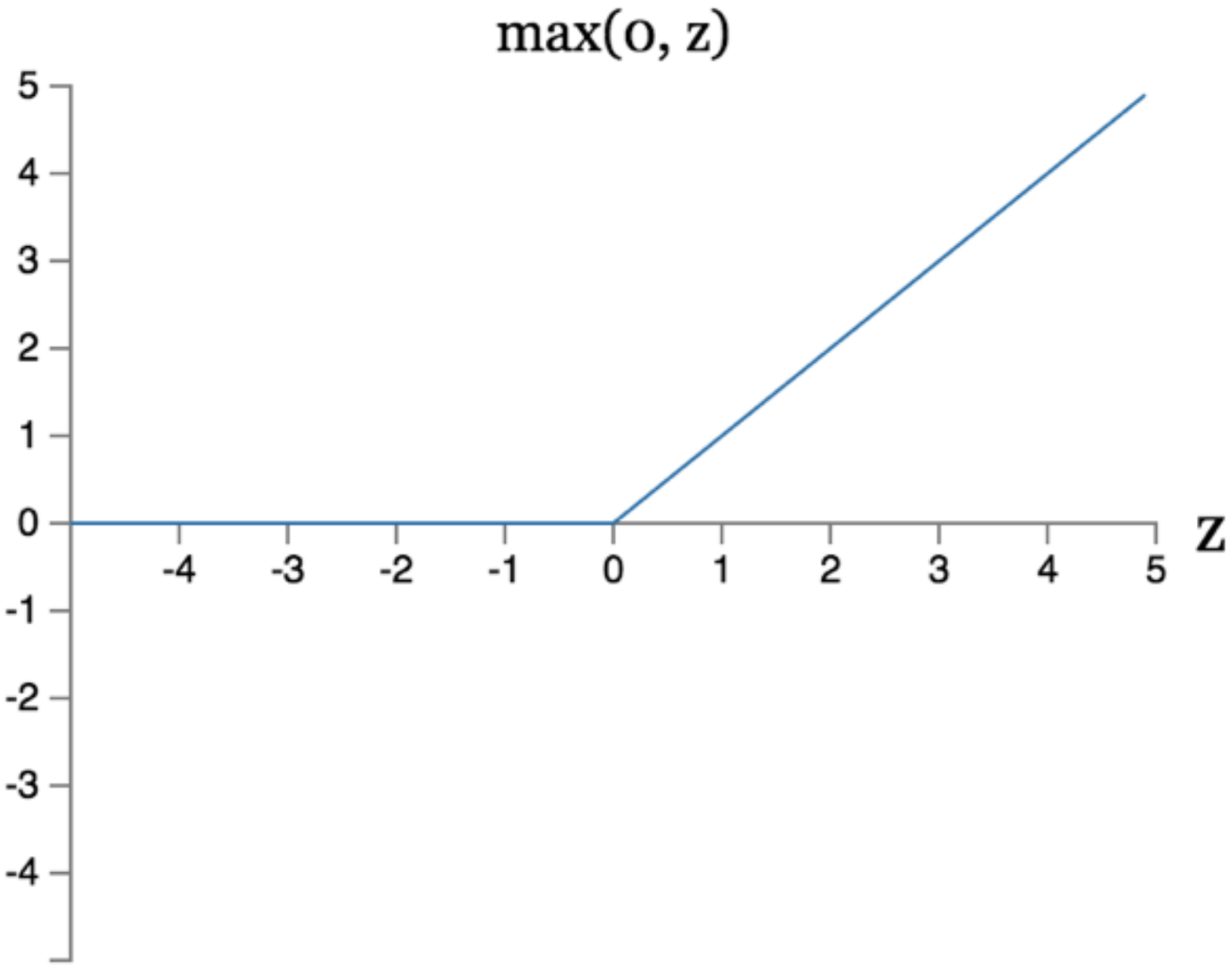
And why now?
GPU and datasets!

Deep Learning II

`Advanced` Neural Network techniques II

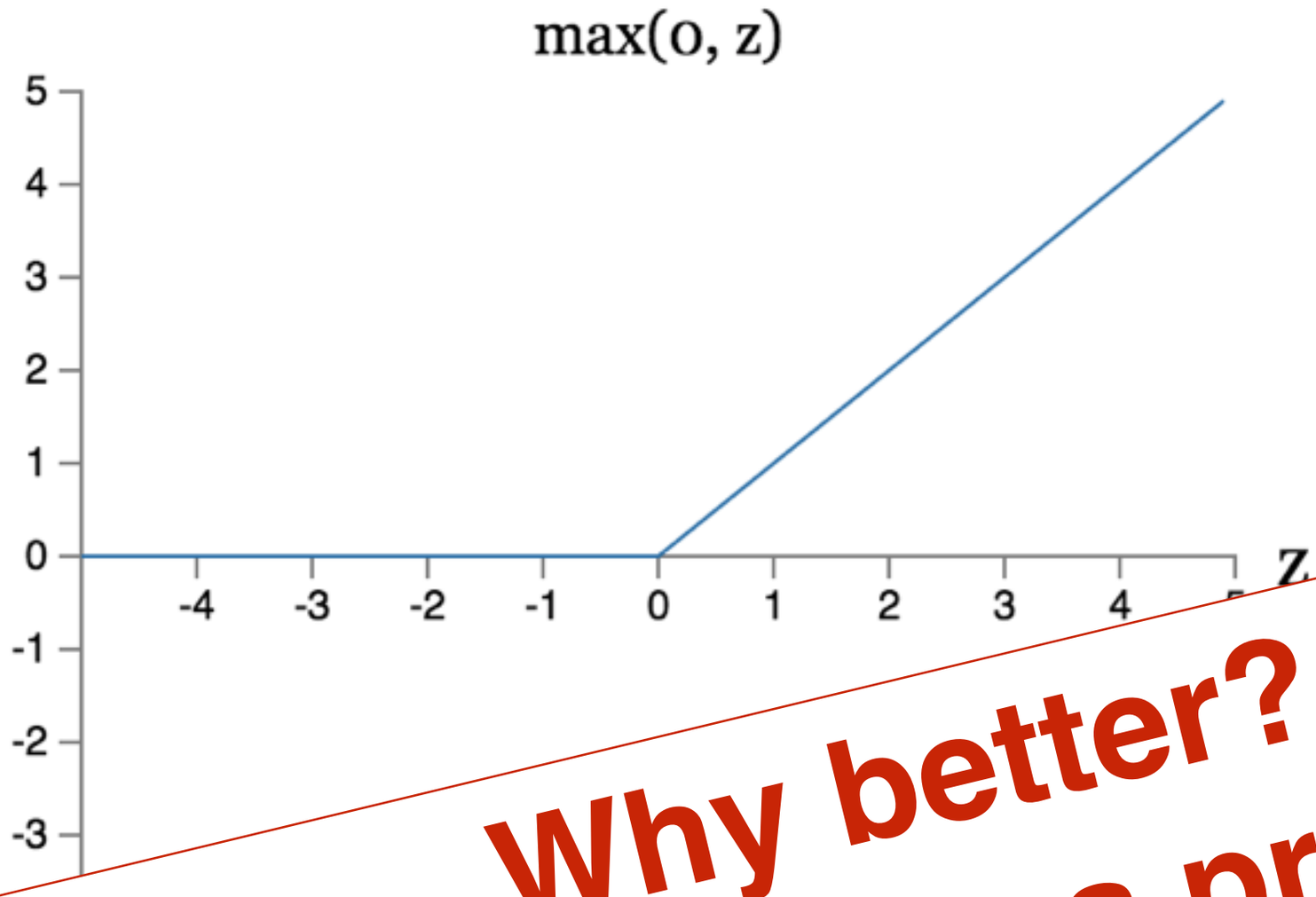
Rectified linear units

A better activation function



Rectified linear units

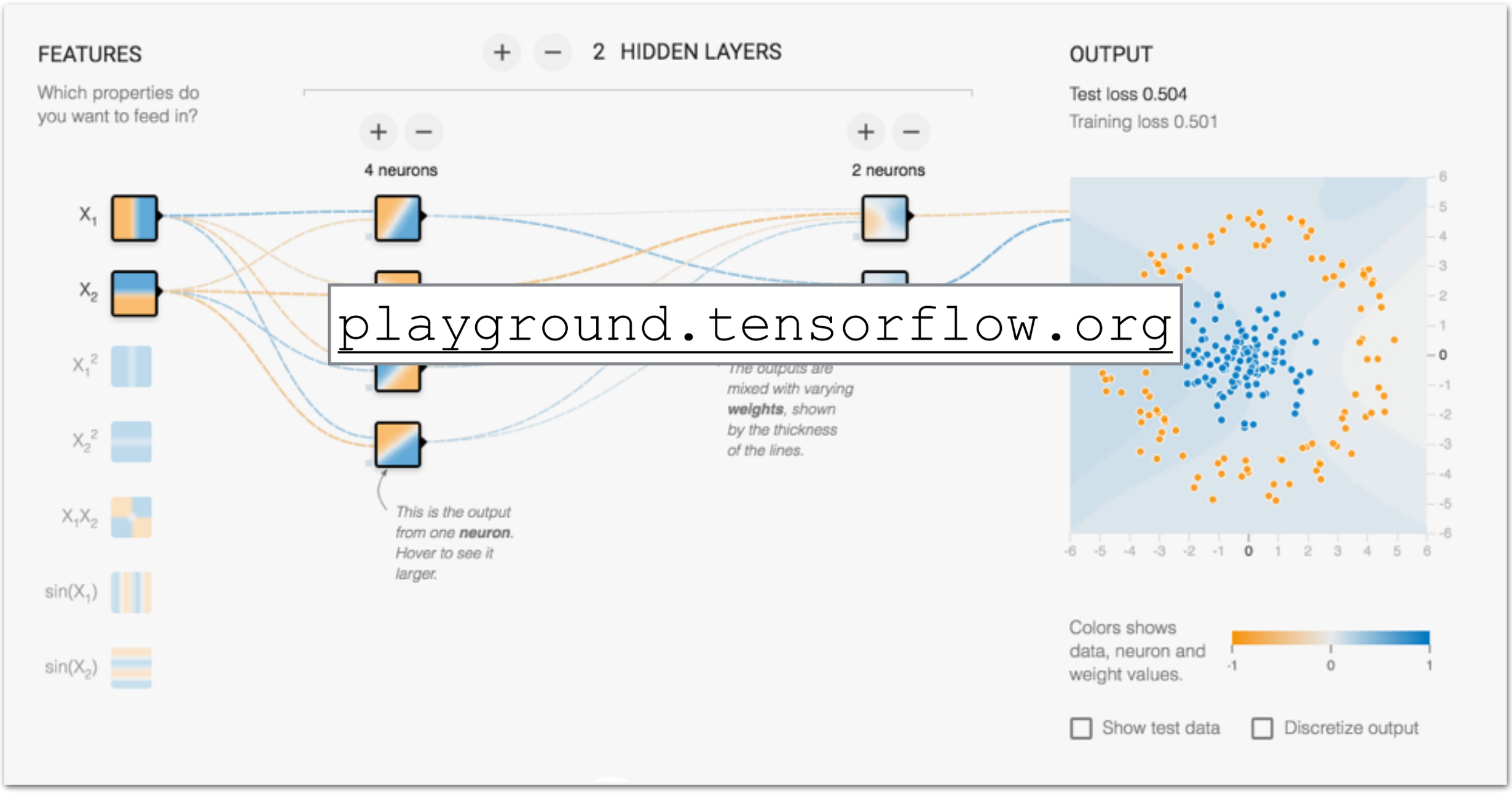
A better activation function



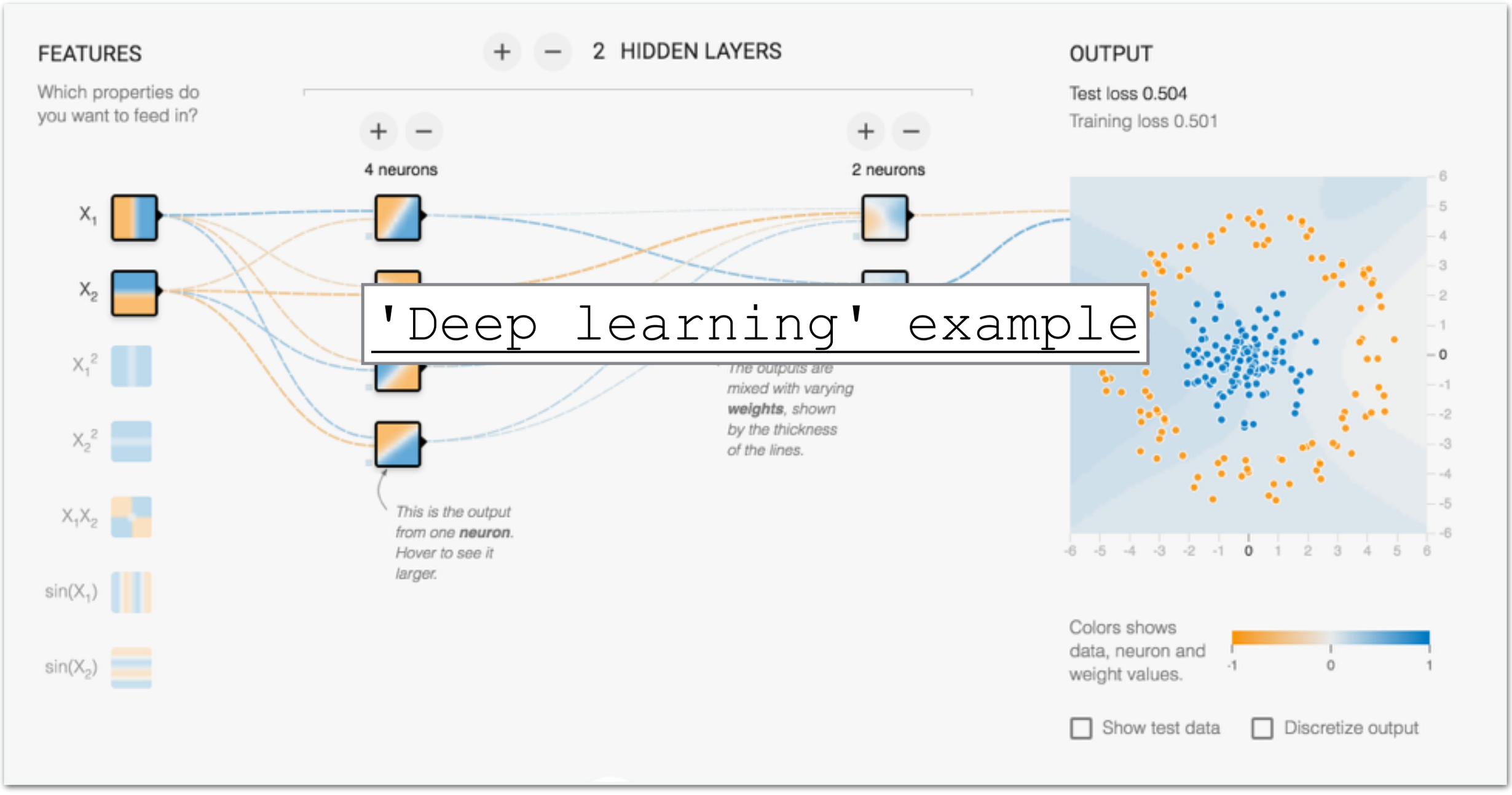
Why better?

What could be a problem?

Tensor flow Playground



Tensor flow Playground



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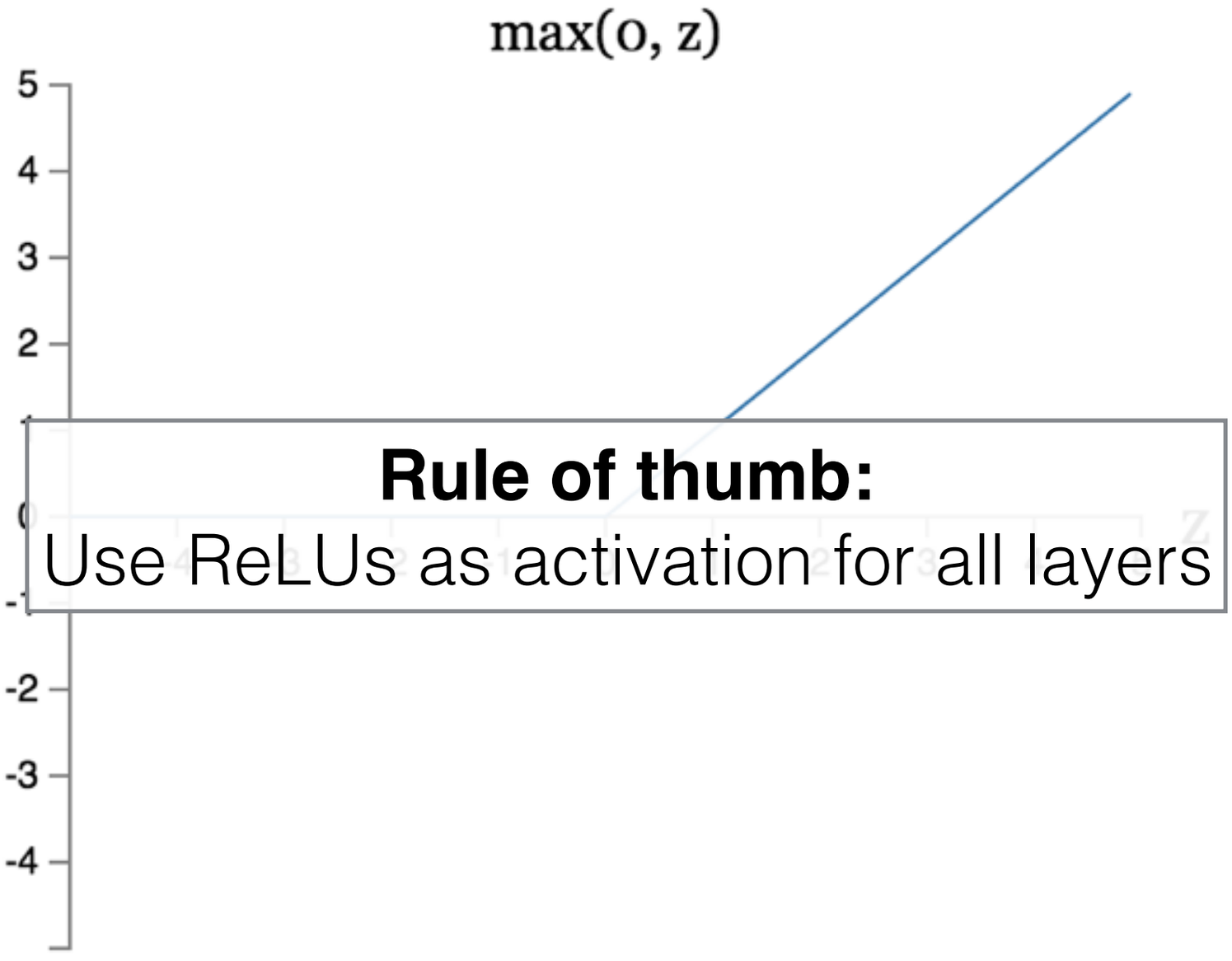


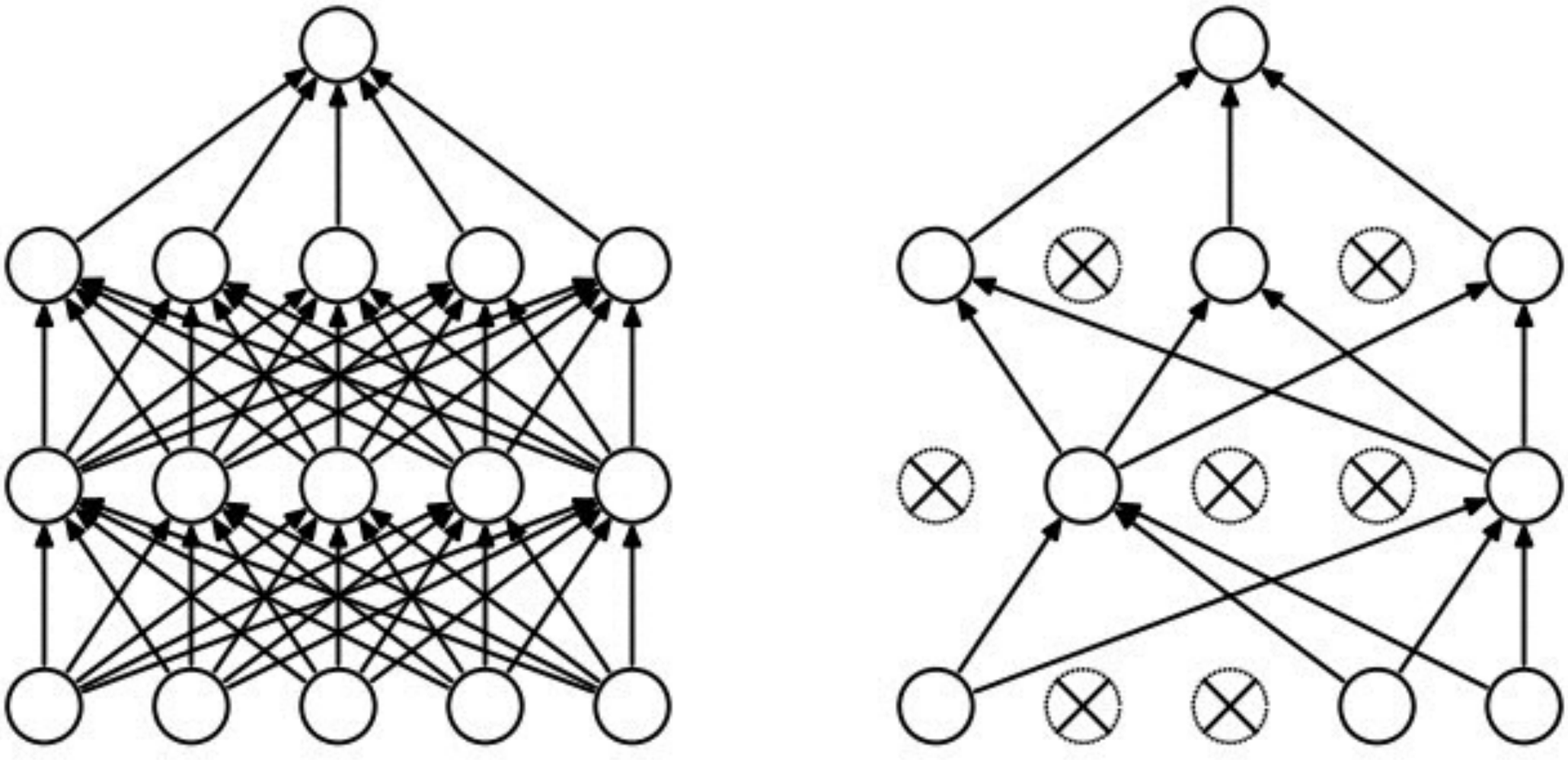
Rule of thumb:

Use ReLUs as activation for all layers

Why does Random Forests work so well?

Regularization with Dropout

random ensembles for NN



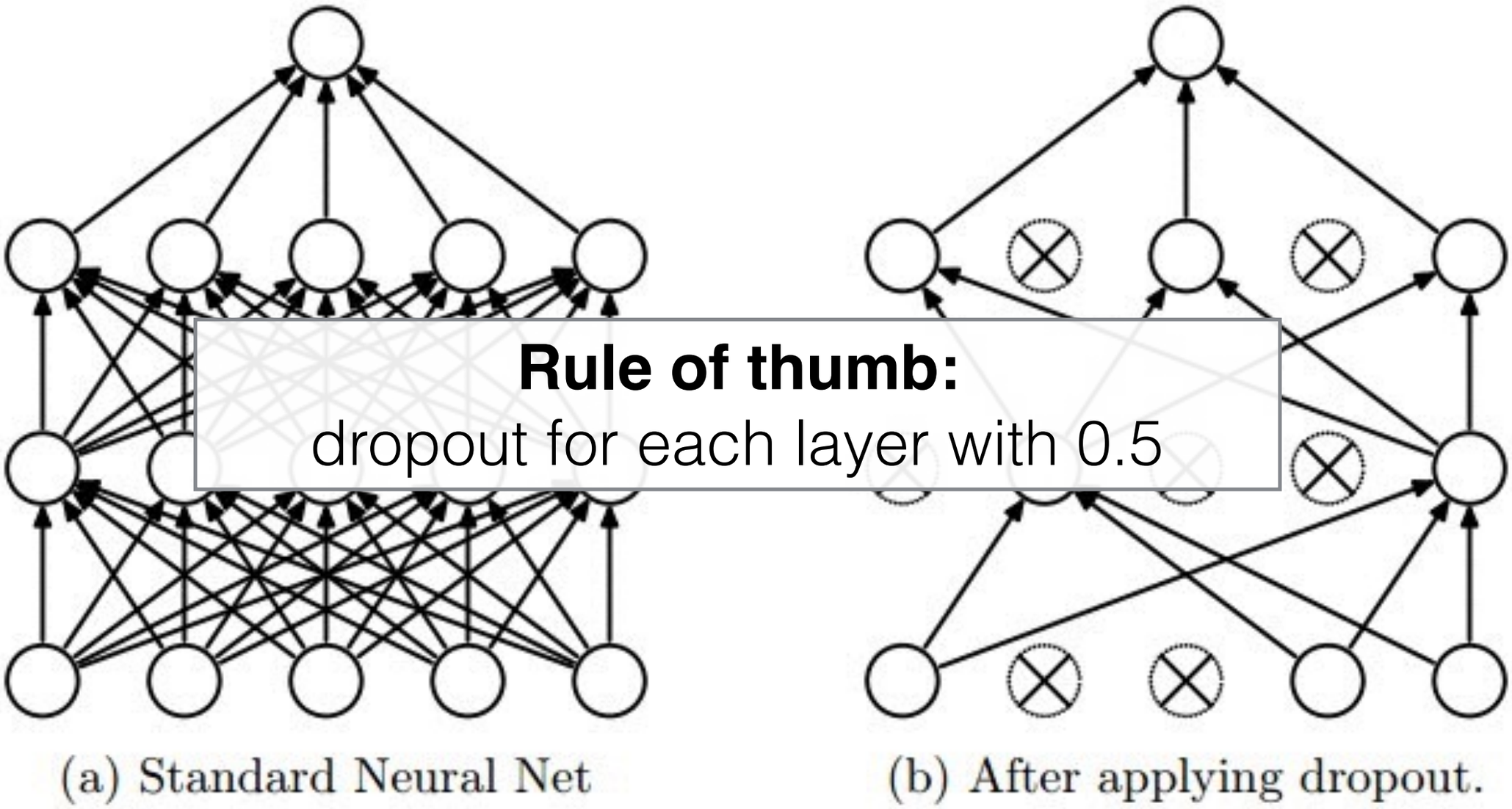
(a) Standard Neural Net

(b) After applying dropout.

Paper: “Dropout: A Simple Way to Prevent Neural Networks from Overfitting”

Regularization with Dropout

random ensembles for NN



(a) Standard Neural Net

(b) After applying dropout.

Rule of thumb:
dropout for each layer with 0.5

Paper: “Dropout: A Simple Way to Prevent Neural Networks from Overfitting”

Pimp my Gradient Descent

Decaying the learning rate

- Every n-epochs by a constant factor
- Every step exponentially
- When the learning stalls
- ….

Gradient Descent

$$w \rightarrow w' = w - \eta \nabla C$$

∇C = gradient of C
w = old weight
w'= new weight
η = learning rate (greek eta)

Gradient Descent and ravines

http://sebastianruder.com/optimizing-gradient-descent/

$$w \rightarrow w' = w - \eta \nabla C$$

∇C = gradient of C
w = old weight

w'= new weight
η = learning rate (greek eta)

Gradient Descent with Momentum

$$v \rightarrow v' = \mu v - \eta \nabla C$$

$$w \rightarrow w' = w + v'.$$

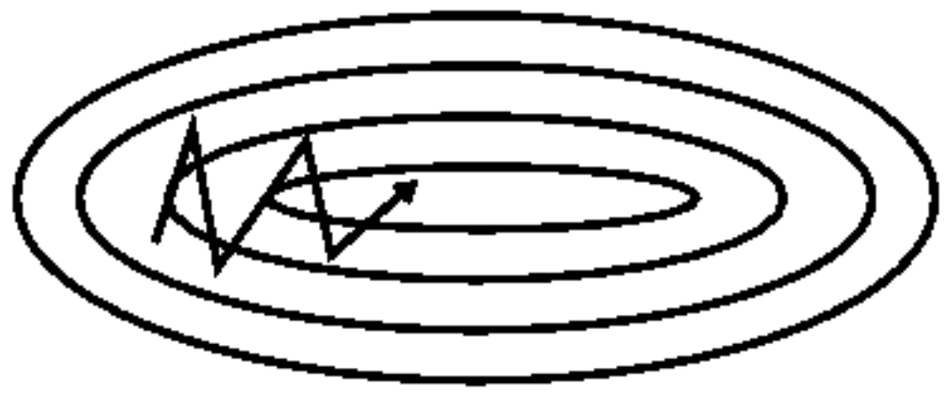
∇C = gradient of C
w = old weight
w'= new weight
η = learning rate (greek eta)

v = old velocity
v' = new velocity
μ = momentum co-efficent or friction (greek mu)

Gradient Descent with Momentum

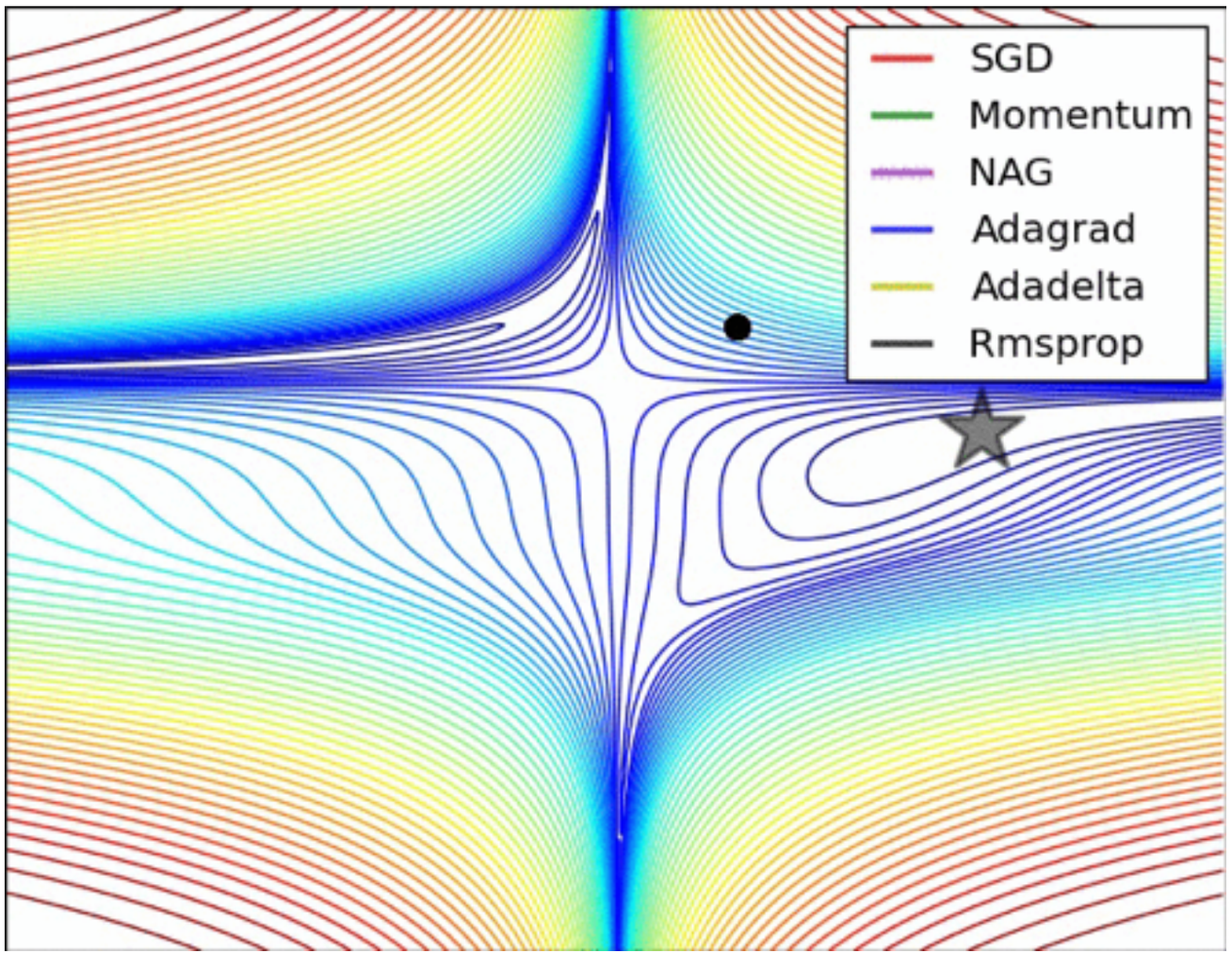
vanilla GD

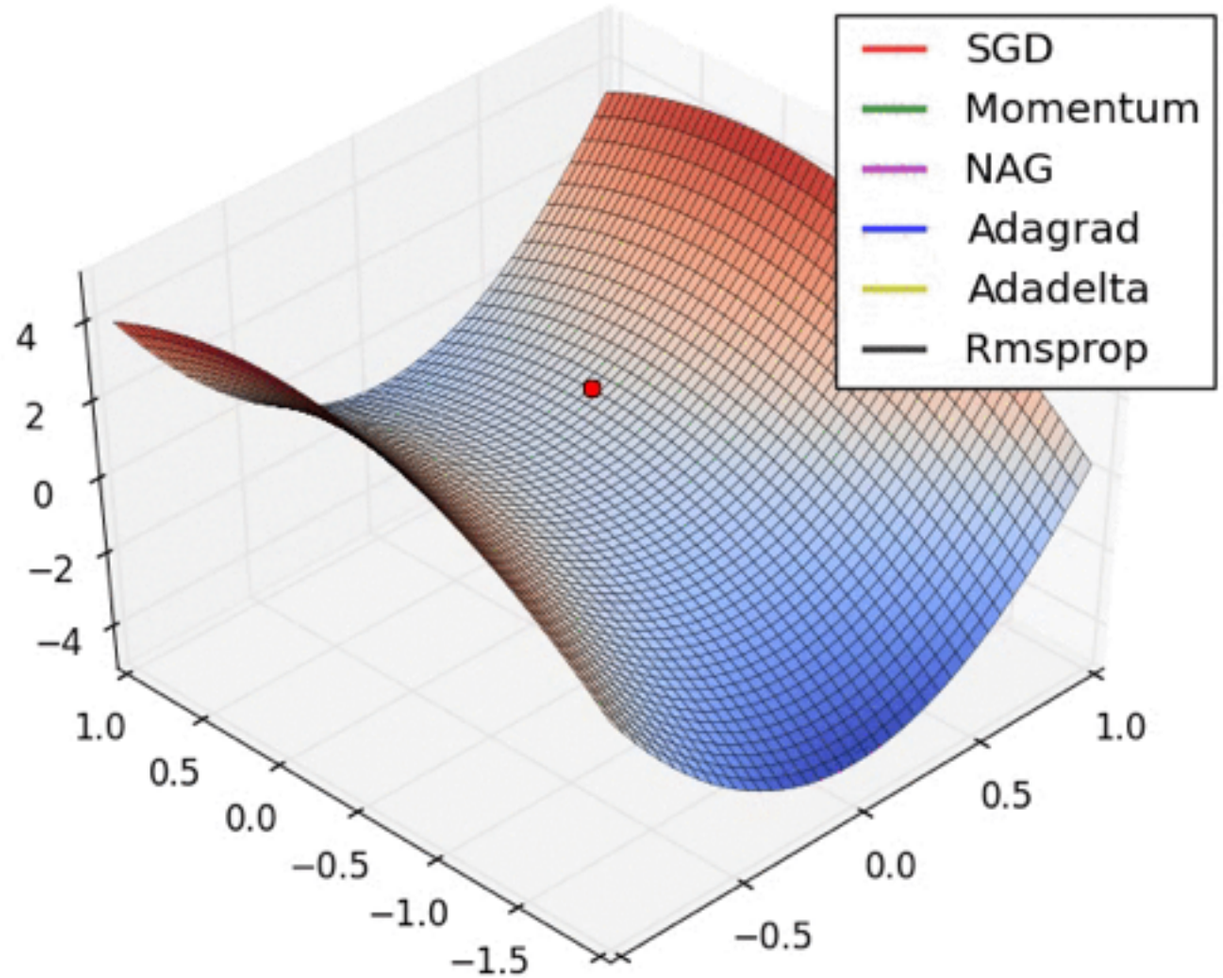
momentum SGD



http://sebastianruder.com/optimizing-gradient-descent/

But there are so many others…





https://twitter.com/alecrad

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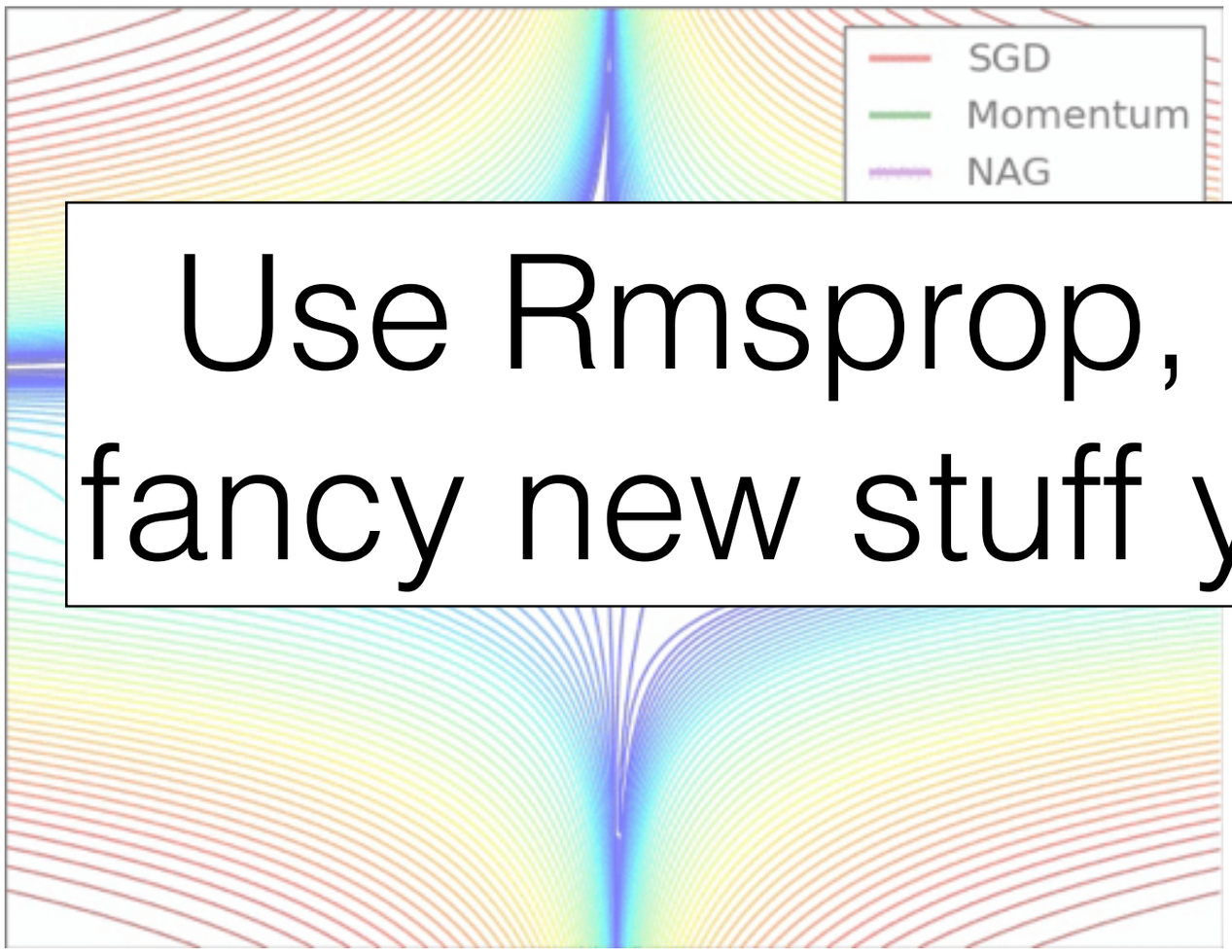

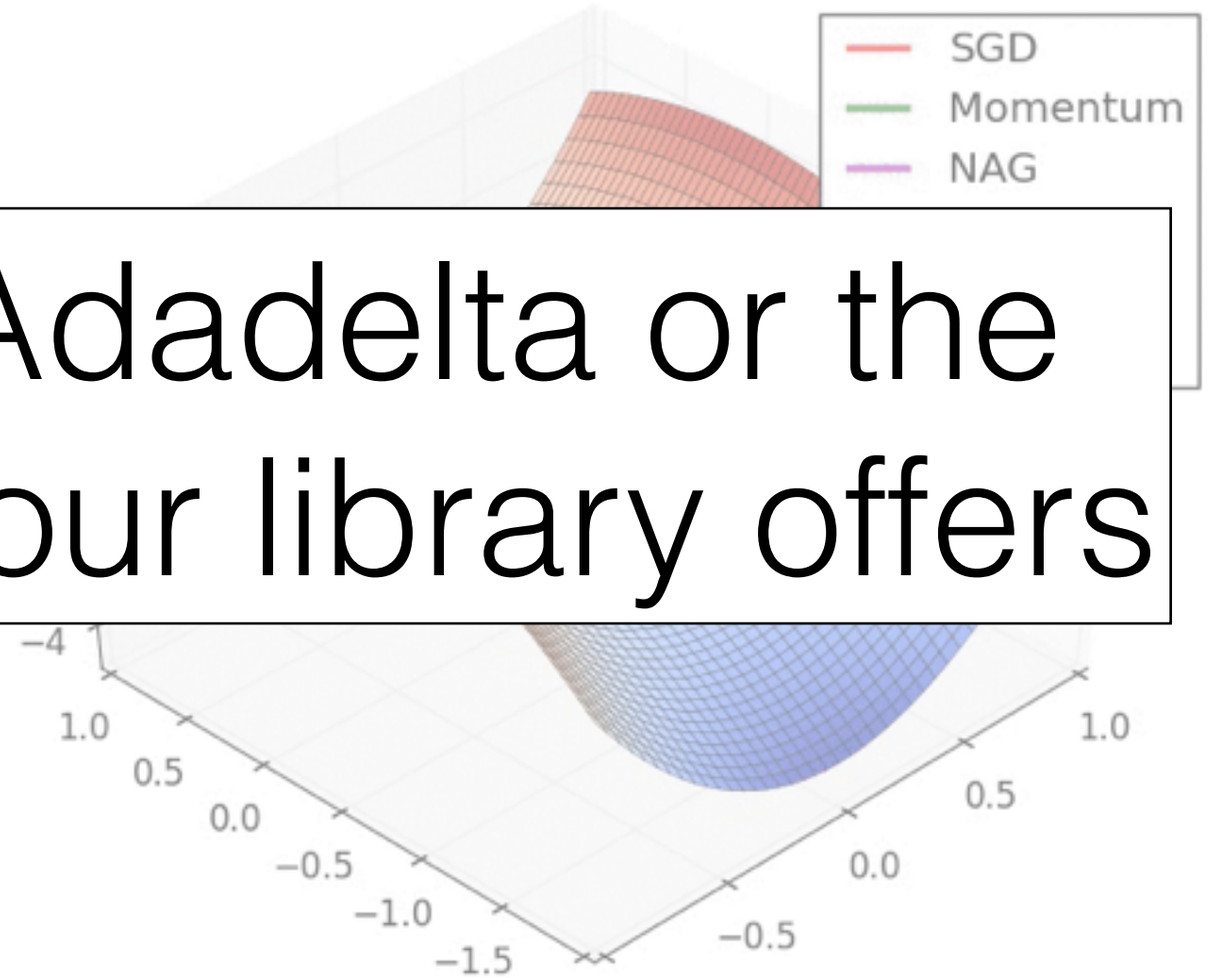

Use Rmsprop, Adadelta or the fancy new stuff your library offers

https://twitter.com/alecrad

back to

PROGRAMMING

Try out :

- dropout
- ReLUs
- **Different optimizers**
- **https://keras.io/**

`~/keras_mnist.ipynb`

Deep Learning and data sets

MNIST (1998)

- Hand written digits (0-9)
- Collected by the United States' National Institute of Standards and Technology, NIST
- Pre segmented
- 28x28 pixel in size
- 60k train, 10k test
- ('M' stands for modified)

MNIST 1998

Eric Jonas
@stochastician

Follow

my advisor: “MNIST is a unit test”

9:39 PM - 25 Jan 2016

7 11

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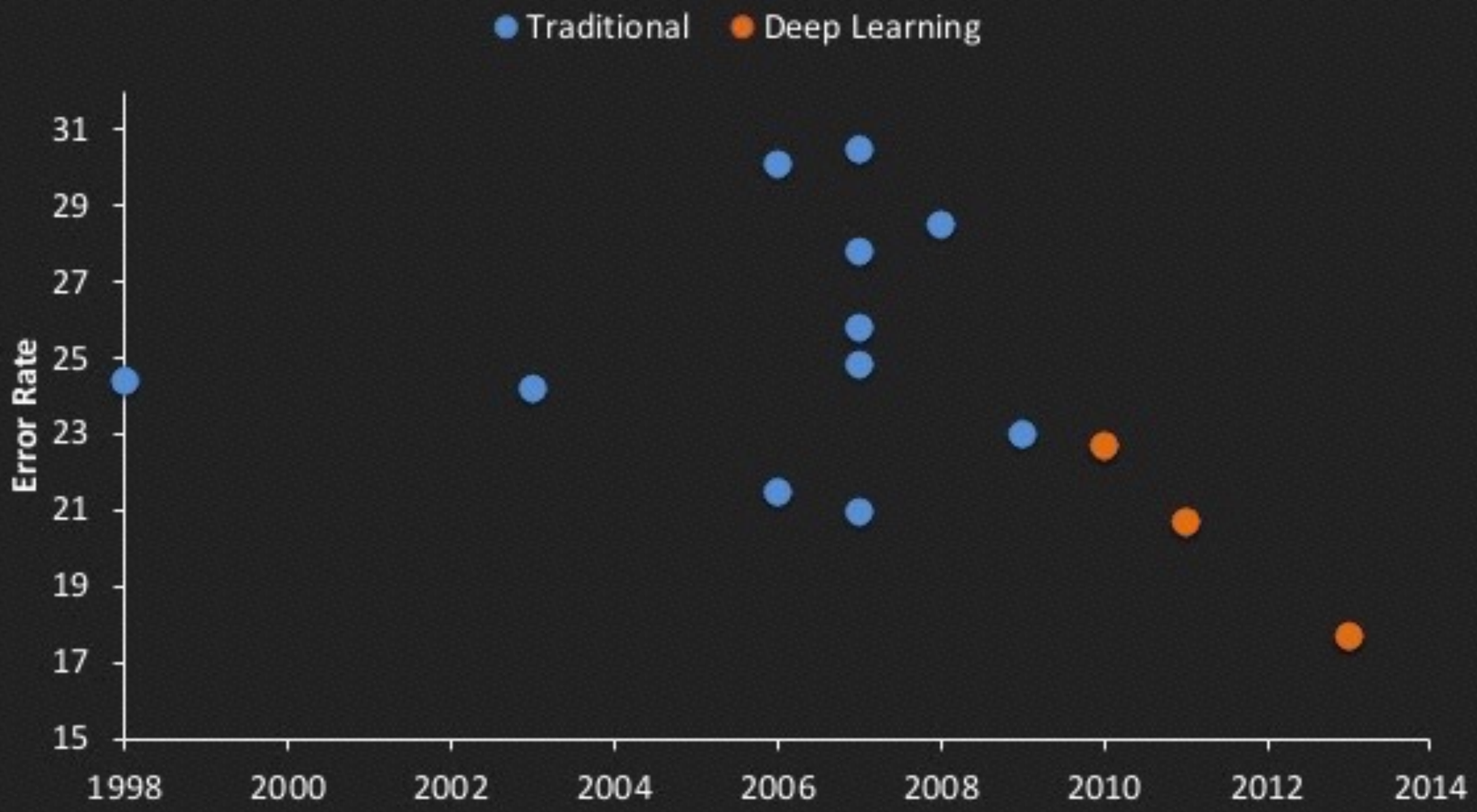
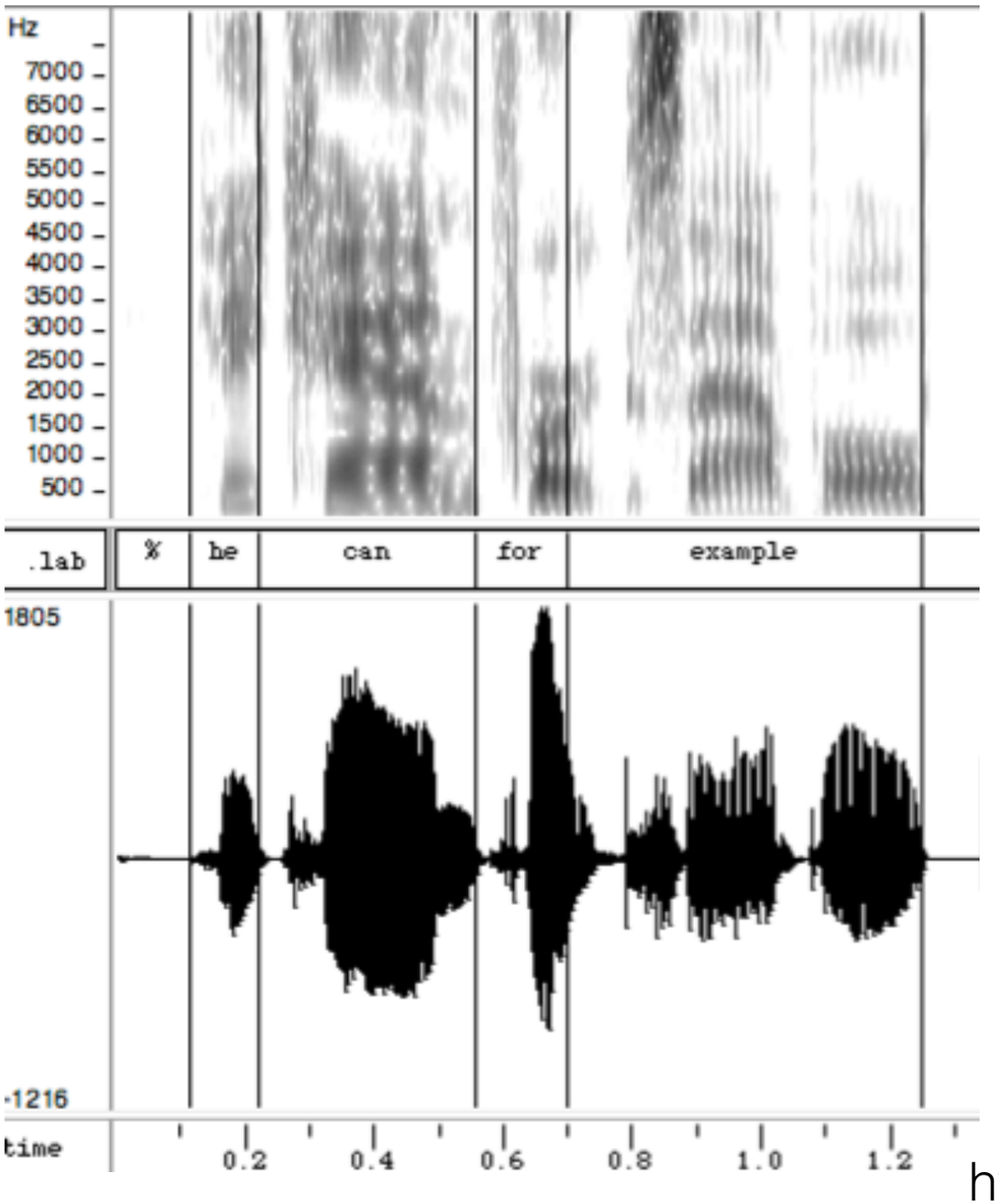
TIMIT Speech Recognition



clarifai

TIMIT (1990)



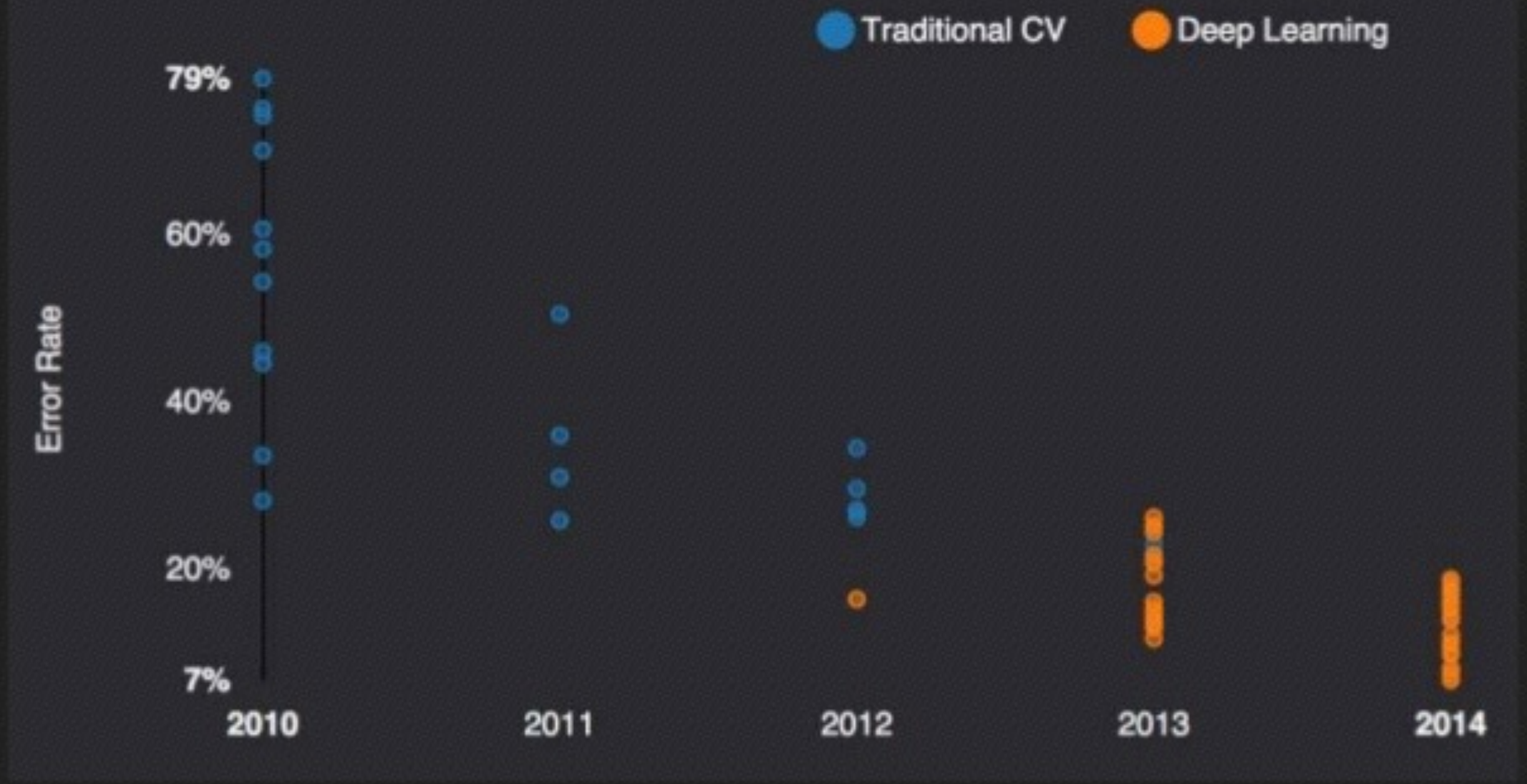
- Texas Instruments (TI) and Massachusetts Institute of Technology (MIT)
- 10 english sentences
- 630 speakers
- tagged on phone level
- 61 different phones
- 5.4h material
- @16 kHz with 16 bit

➡ (~400m samples)

➡ https://catalog.ldc.upenn.edu/LDC93S1

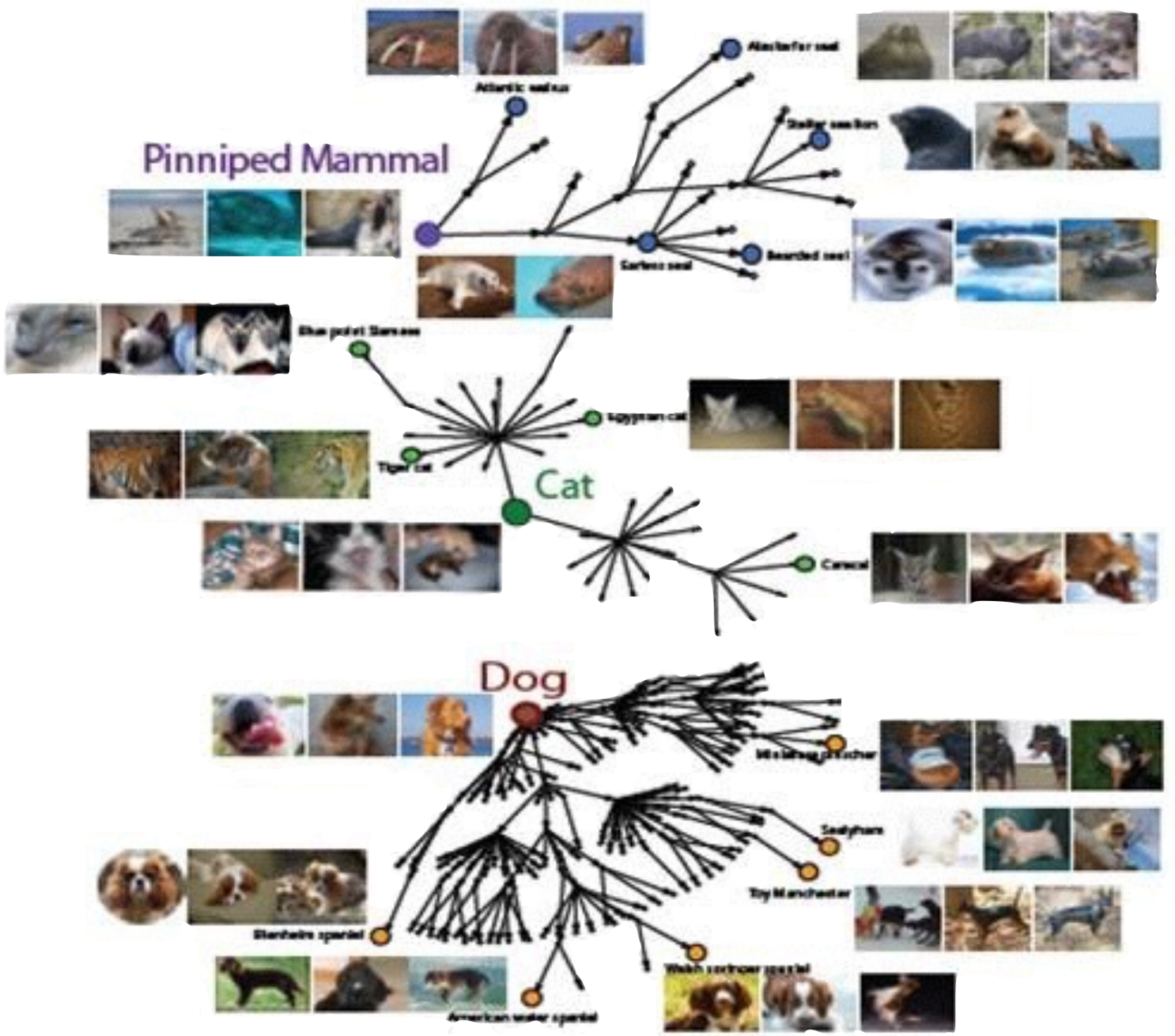
http://languagelog.ldc.upenn.edu/nll/?p=8116

ImageNet Error Rate 2010-2014



clarifai

‘Imagenet’ (2012)



Precise name: **Large Scale Visual Recognition Challenge**

- 1m images
- 1k concepts
- subset of the Imagenet
  - 20m images
  - 10k concept (tree structure)
  - still growing
  - image-net.org

http://web.eecs.umich.edu/~jiadeng/

‘MS COCO’ (2014)

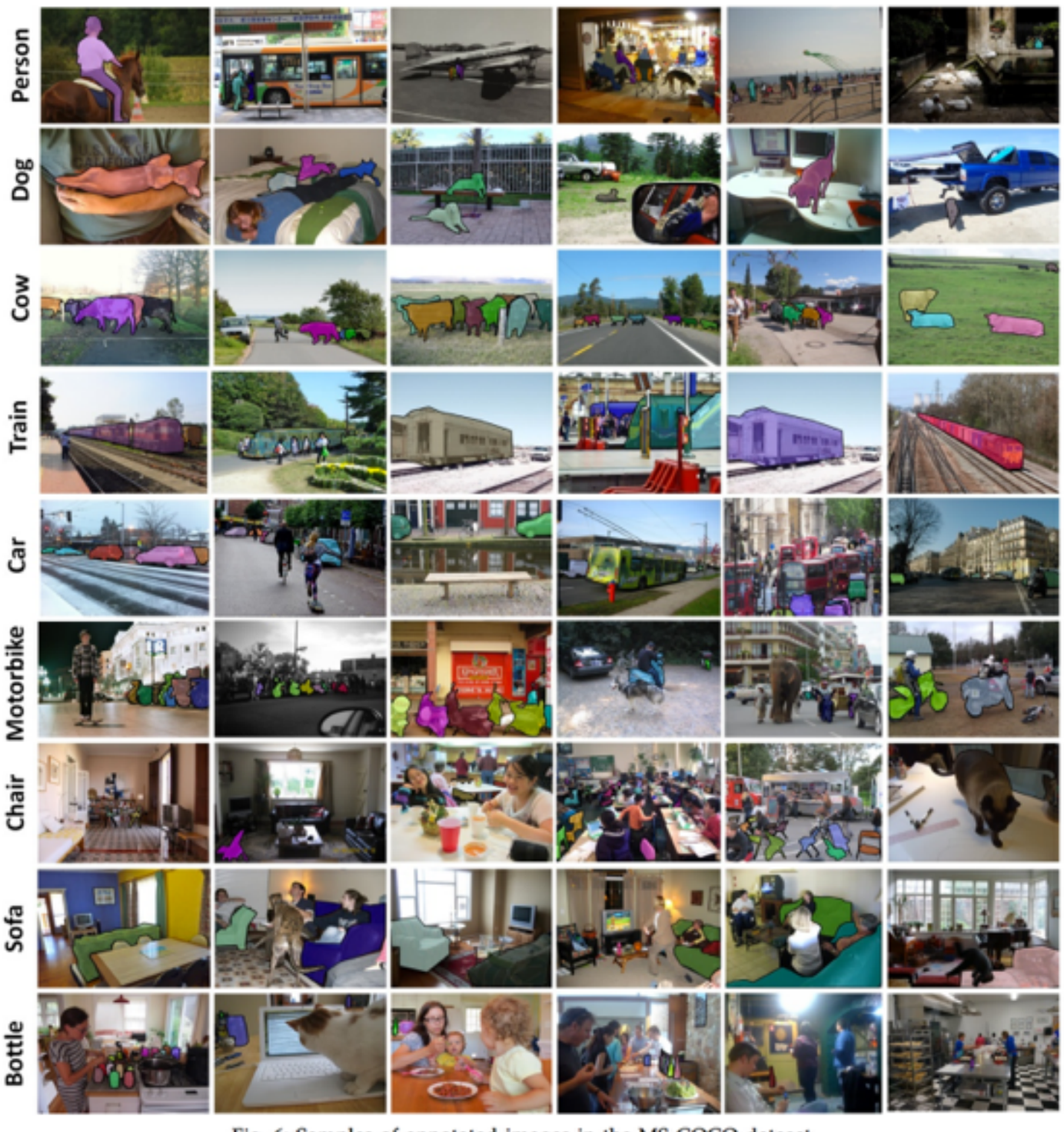
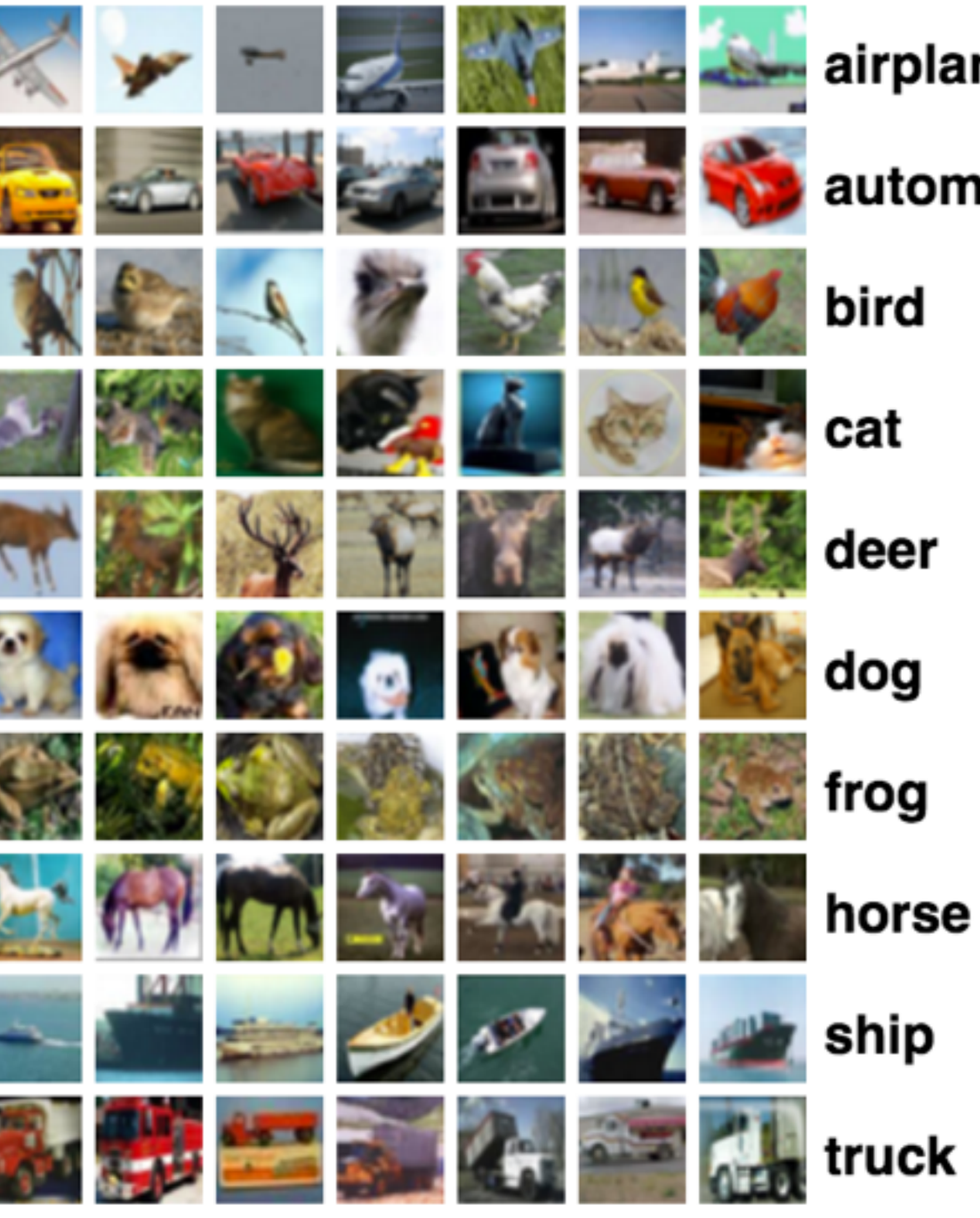


Fig. 6: Samples of annotated images in the MS COCO dataset.

Precise name: **Microsoft’s Common Objects in COntext**

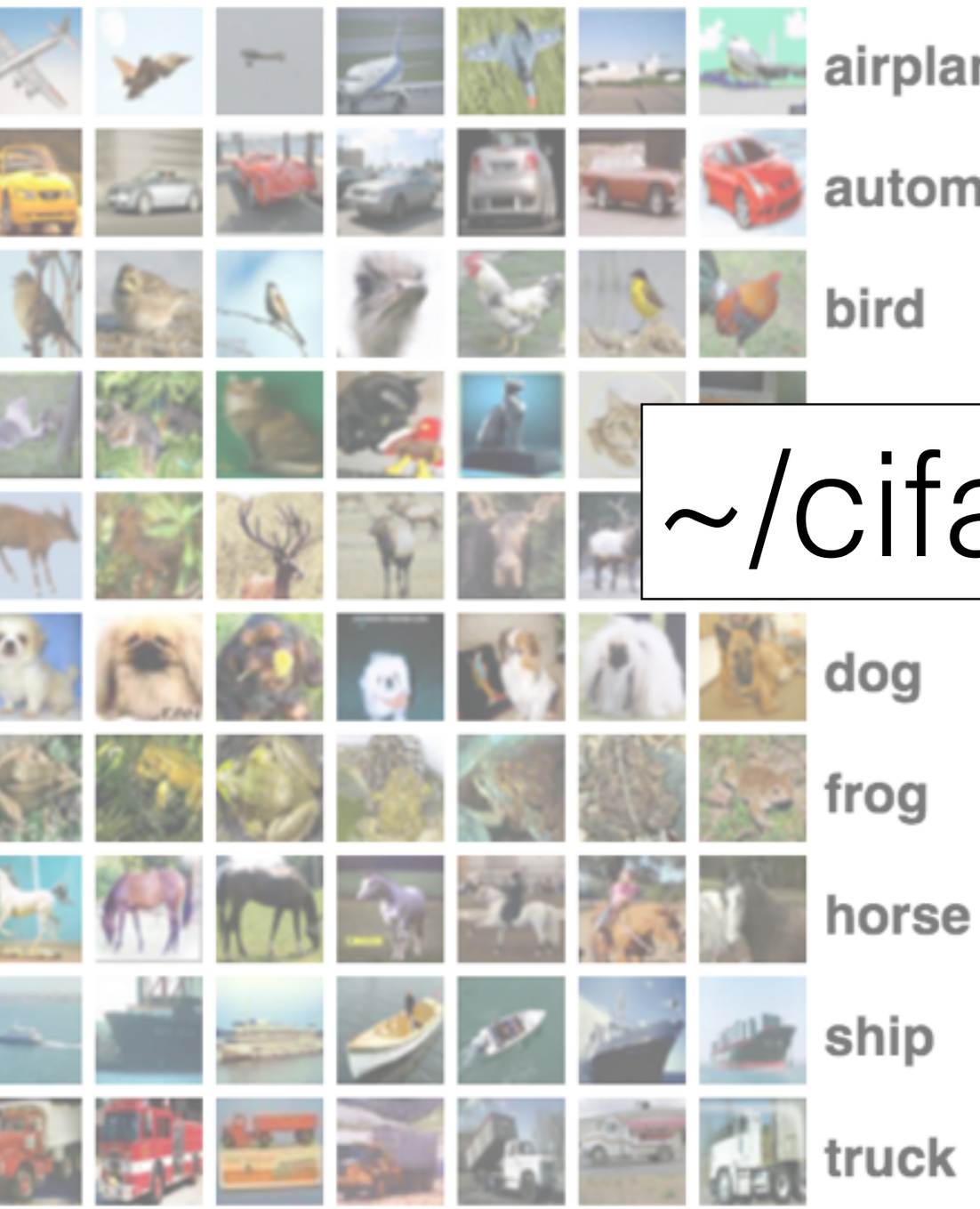
- More than 70 categories
- Object segmentation
- Multiple objects per image
- More than 300k images (150k)
- **5 captions per image**
- mscoco.org

CIFAR-10



- CIFAR stands for C*anadian Institute for Advanced Research*
- 10 concepts
- 6000 images per concept
- Image size is 32x32x3
- Part of the 80 Million Tiny Images dataset
- https://www.cs.toronto.edu/~kriz/cifar.html

CIFAR-10



~/cifar10.ipynb

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Cat or dog?

Or how to work with little data

Cat or dog?

Or how to work with little data

~/cats+dogs/train/cats/…

from: www.kaggle.com/c/dogs-vs-cats

Cat or dog?

Or how to work with little data

~/cats+dogs/first_try.ipynb

from: www.kaggle.com/c/dogs-vs-cats

The trick

The ‘trick’

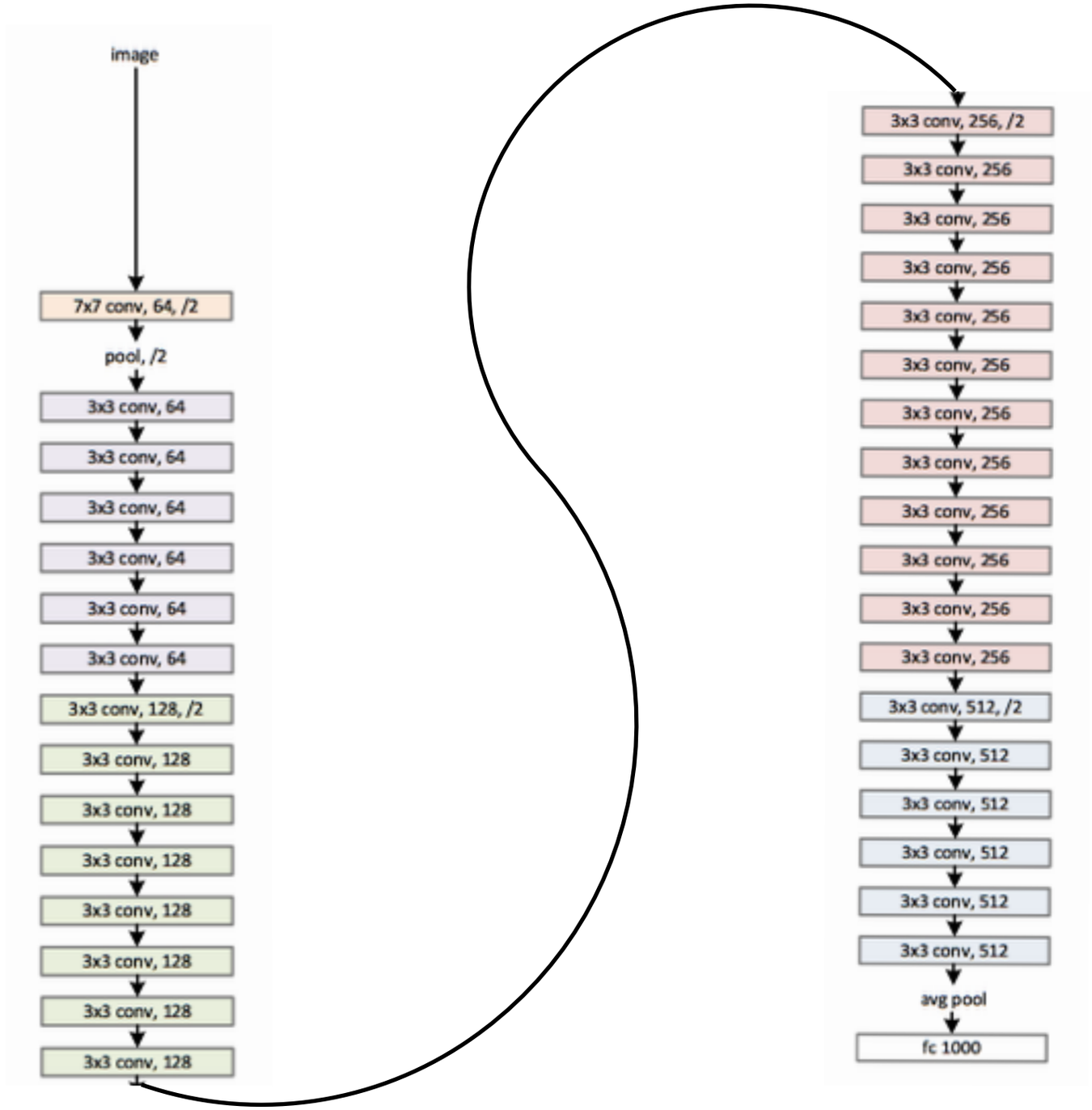
image
7x7 conv, 64, /2
pool, /2
3x3 conv, 64
3x3 conv, 64
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3x3 conv, 64
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3x3 conv, 64
3x3 conv, 128, /2
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128
3x3 conv, 256, /2
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 512, /2
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3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
avg pool
fc 1000

The ‘trick’

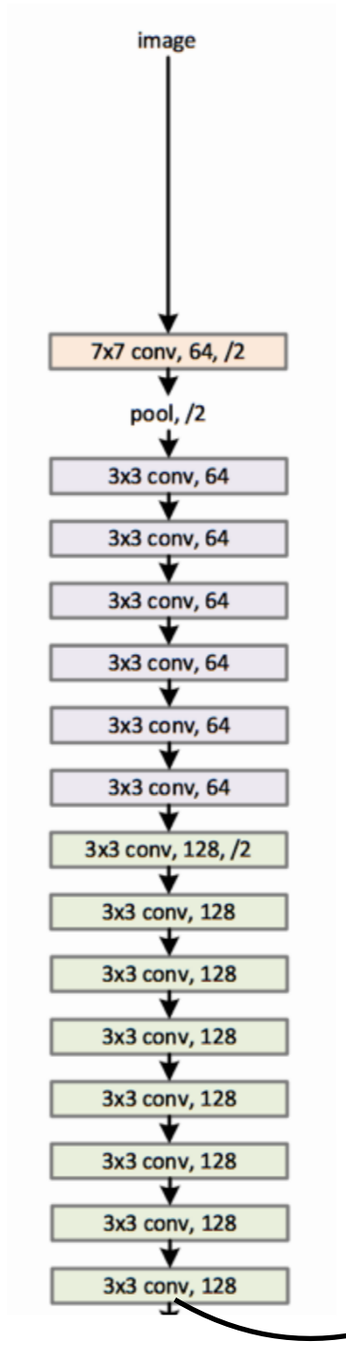
image
7x7 conv, 64, /2
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3x3 conv, 64
3x3 conv, 128, /2
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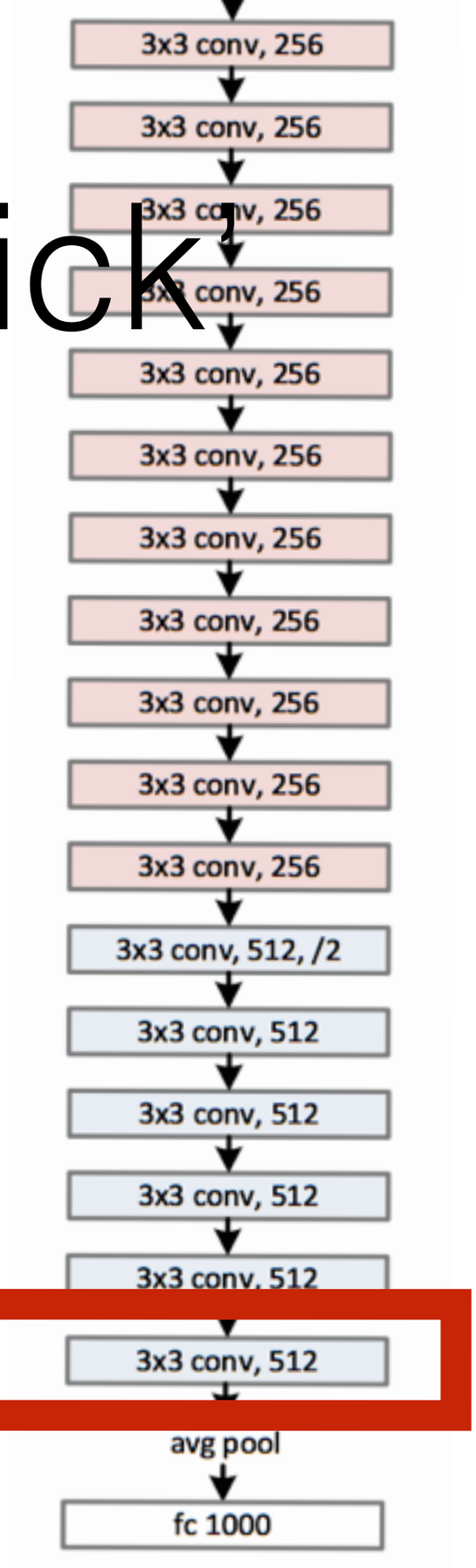
3x3 conv, 128


3x3 conv, 256
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3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 512, /2
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3x3 conv, 512
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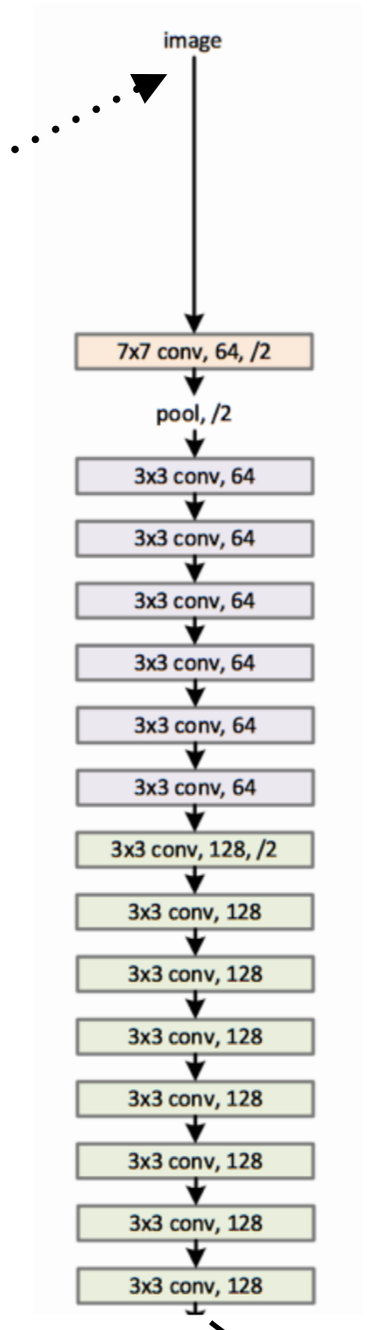
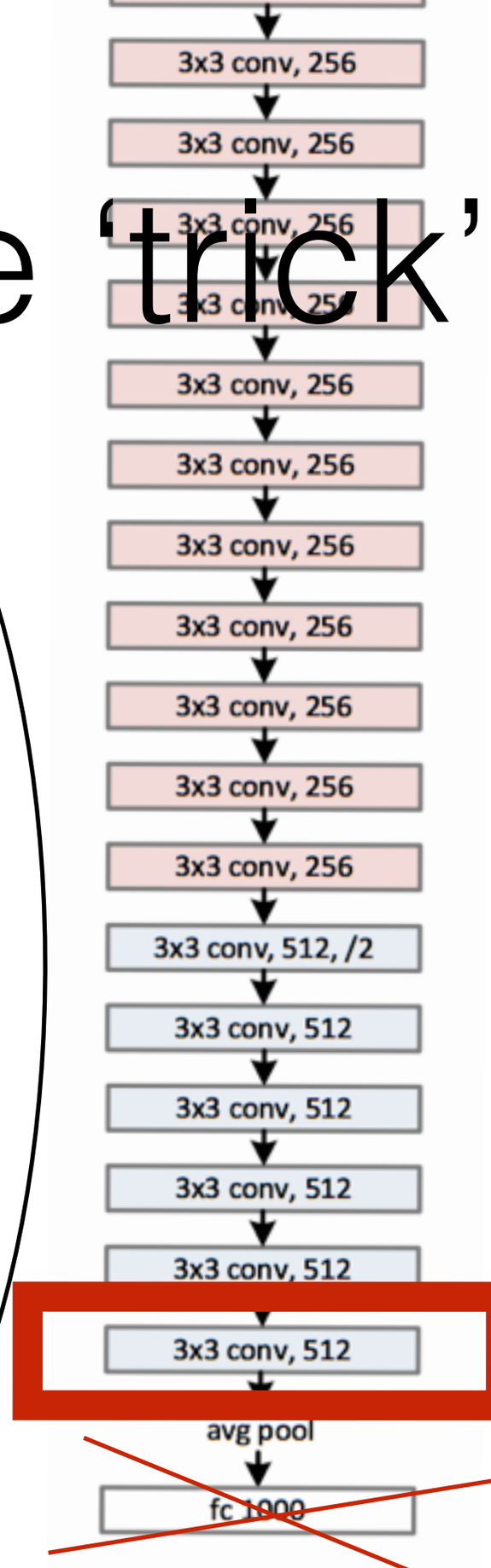
The ‘trick’

images

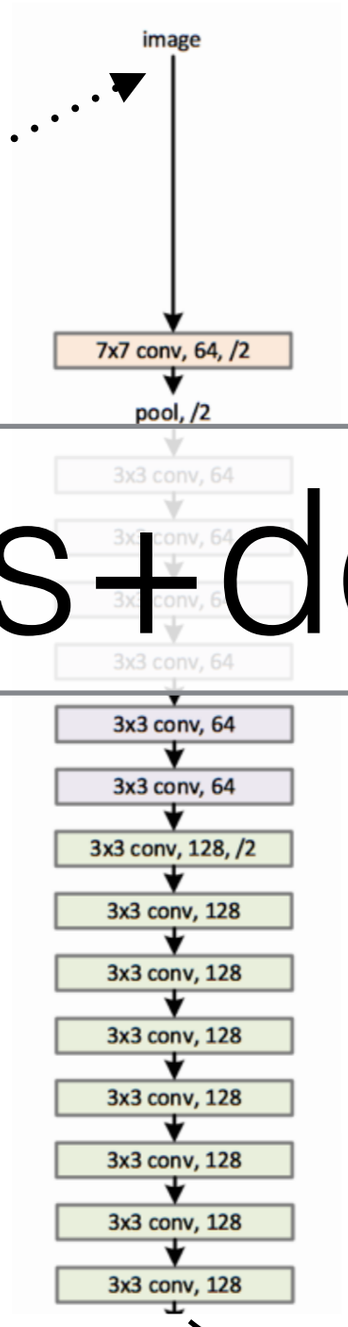


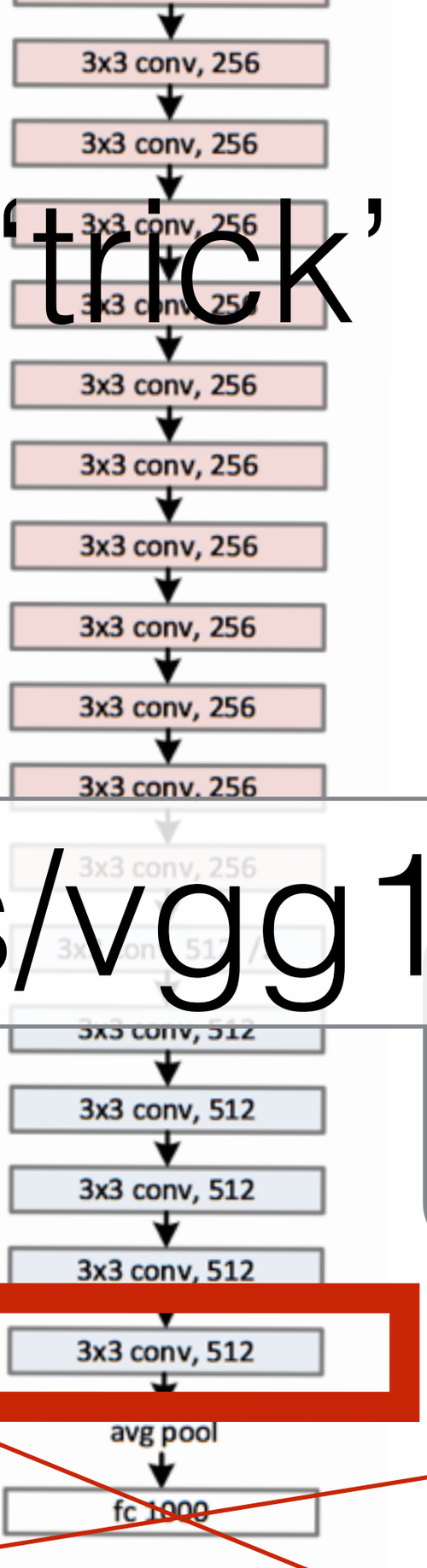


predictions

SVM | RF | NN| …

The ‘trick’



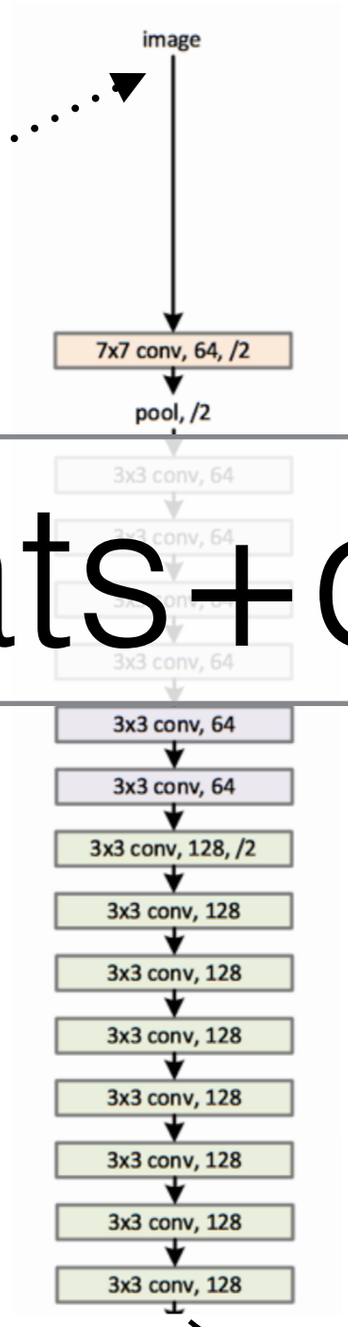


predictions

SVM | RF | NN| …

~/cats+dogs/vgg16.ipynb

The ‘trick’



predictions

SVM | RF | NN| …

~/cats+dogs/trick.ipynb

The ‘trick’

Using pre-trained weights of as feature extractor in combination with an familiar classifier like SVM or RF.

Pros

- predictable training time
- learned features
- needs less data

Cons

- needs pre-trained network weights
- introduction of bias
- reaches not the full potential of Deep Learning

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~/cats+dogs/trickier.ipynb

Q: How do I know what architecture to use?

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A: Don’t be a hero:

1. Take what ever works on ILSVRC (latest ResNet)
2. Download a pretrained model
3. Potentially add/delete some parts of it
4. Finetune to your application

Karpathy at BayArea DL School 2016

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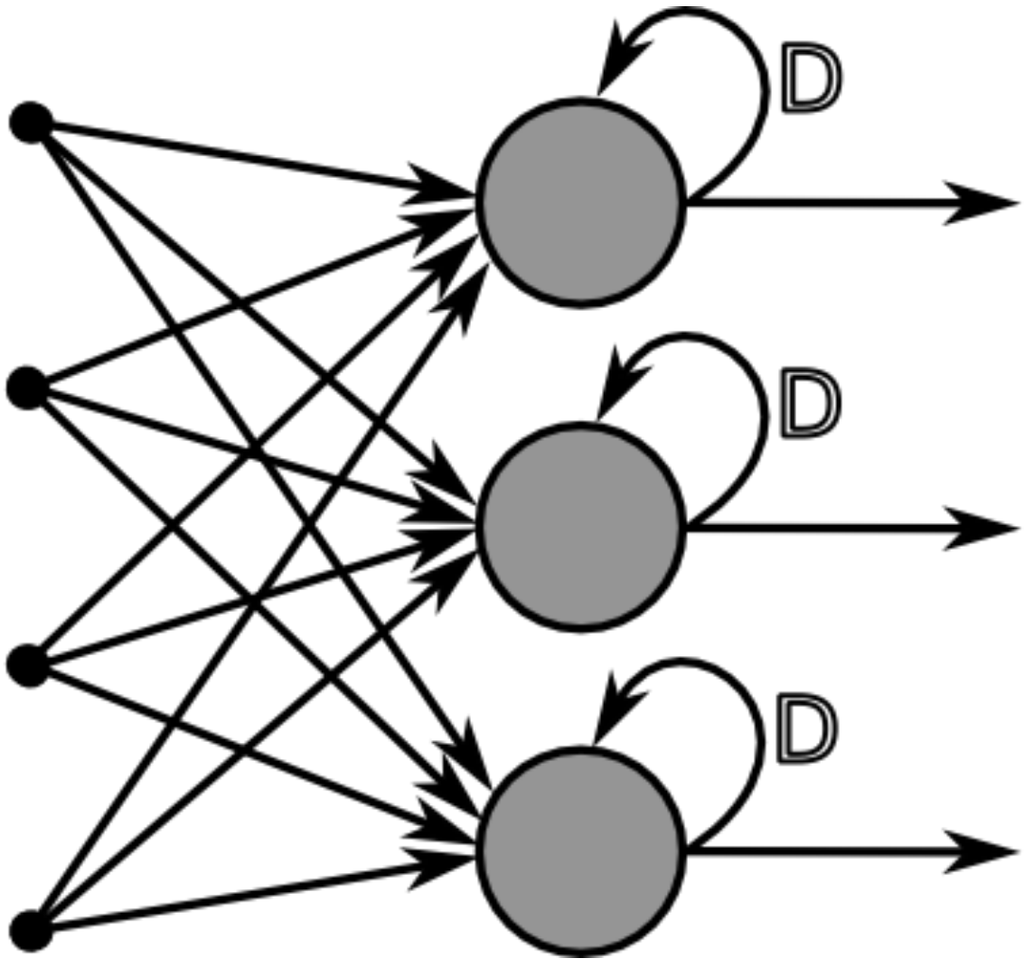
Architecture engineering
is the new *Feature engineering*

Karpathy at BayArea DL School 2016

Other Deep Learning approaches

Recurrent Neural Networks (RNN)



- Good for time series problems
  - sound
  - hand writing
- unstable
  - vanishing and exploding gradients
- but recent advancement
  - with major breakthroughs in voice recognition (google now, siri, cortana)

https://commons.wikimedia.org/wiki/File:RecurrentLayerNeuralNetwork.png

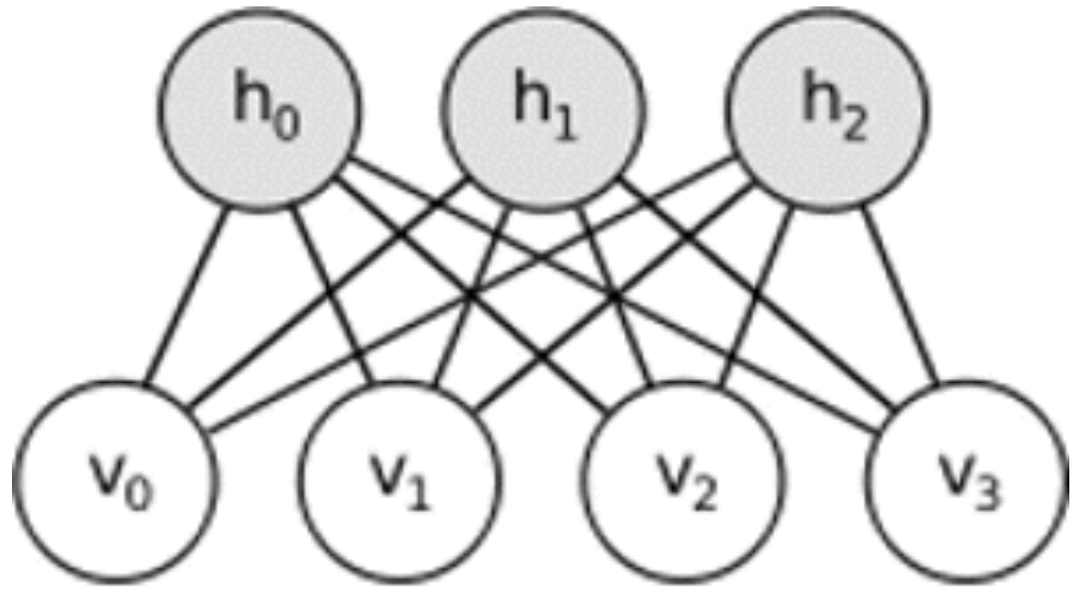
Restricted Boltzman Machines (RMBs)

- are also know as **Deep Believe Networks**

- train a reconstruction of the inputs with fewer parameters

- can be trained unsupervised or semi-supervised

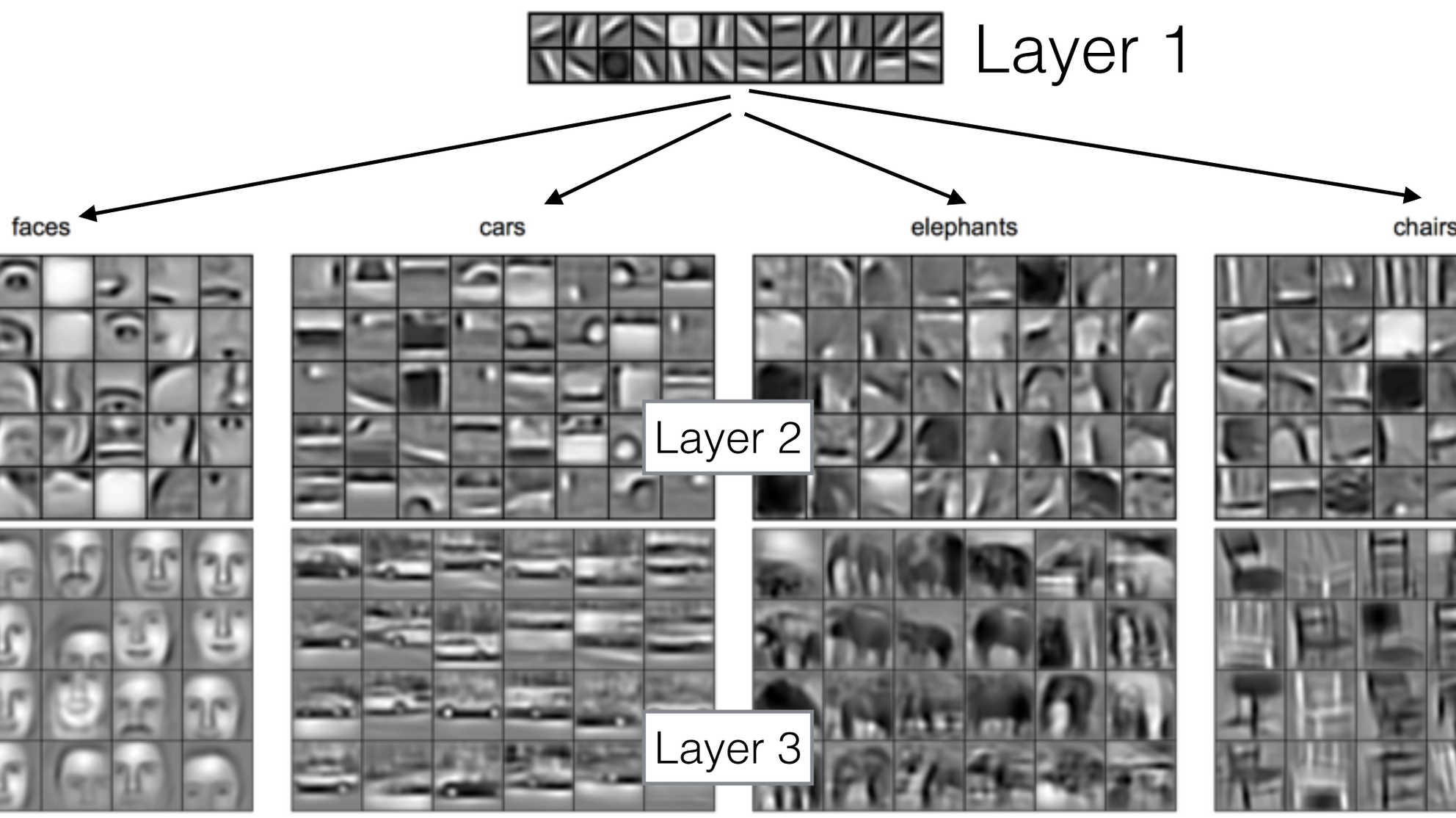
- were the first general-purpose deep architecture that could be trained successfully (2006)



- give easily interpretable nodes

- are now surpassed by CNNs

Convolutional Deep Believe Networks



Paper: Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations

Deep Learning small talk

The Deep Learning Heads

Yan LeCun

- Known for CNNs
- LeNet5 1989 (AT&T)
- Torch / Lua
- now head of Facebook AI Research (working there also with V. Vapnik (SVM))

Geoffrey Hinton

- Co-inventor of the backpropagation in ’74
- Known for DBNs
- University Toronto + 50% google research since 2012
- Vision break through 2012

Yoshua Bengio

Yoshua Bengio

- University Montreal
- Sep 2016: Grant of $93 million to work on "AI"
- Theano

Jürgen Schmidhuber

- Pronounciation:
  You_again Shmidhoobuh
- Known for RNN
- University of Lugano (Switzerland)
- Also working on art theory + generation through NNs

The Neural Computation and Adaptive Perception program

- founded by LeCun, Hinton and Bengio in 2004

- funded by a Canadian Institute for Advanced Research (CIFAR) grant

- invite only

- laid the groundwork and spearheaded the Neural Network renaissance

The Neural Computation and Adaptive Perception program

?

Deep Learning Conspiracy

http://people.idsia.ch/~juergen/deep-learning-conspiracy.html

OpenAI

- non-profit artificial intelligence research company
- founded by 2015 by Elon Musk and Sam Altman (YCombinator)
- ‘1 Billion $ in funding’

“*Carefully promote and develop friendly AI in such a way as to benefit, rather than harm, humanity as a whole.”*

OpenAI

- non-profit artificial intelligence research company

OpenAI's Director of 'Strategy and Communications', Jack Clark, has a very good newsletter about Deep Learning and AI.

Follow it to stay up to date:

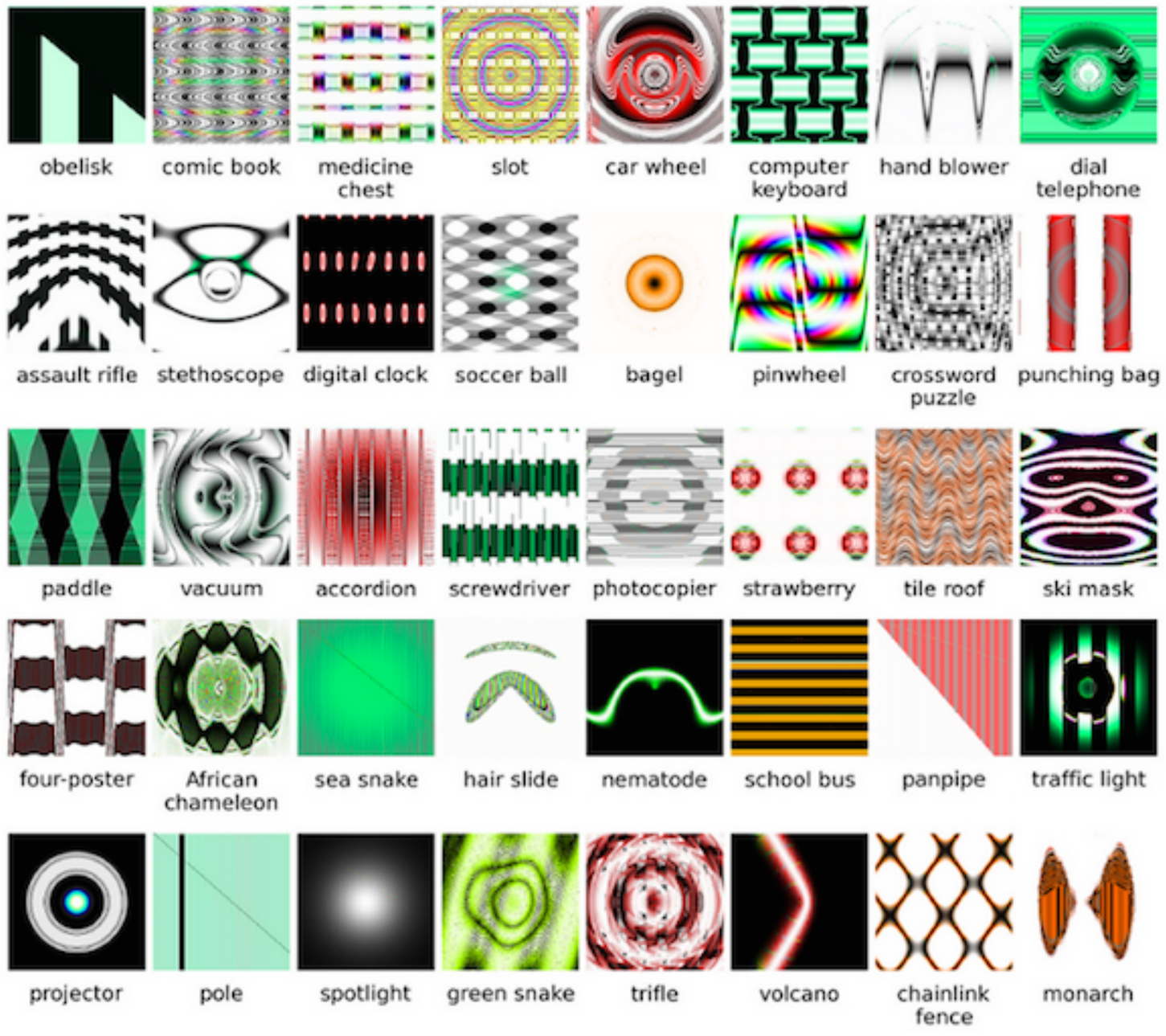
jack-clark.net

whole.

But aren't CNNs actually quite similar to the brain???

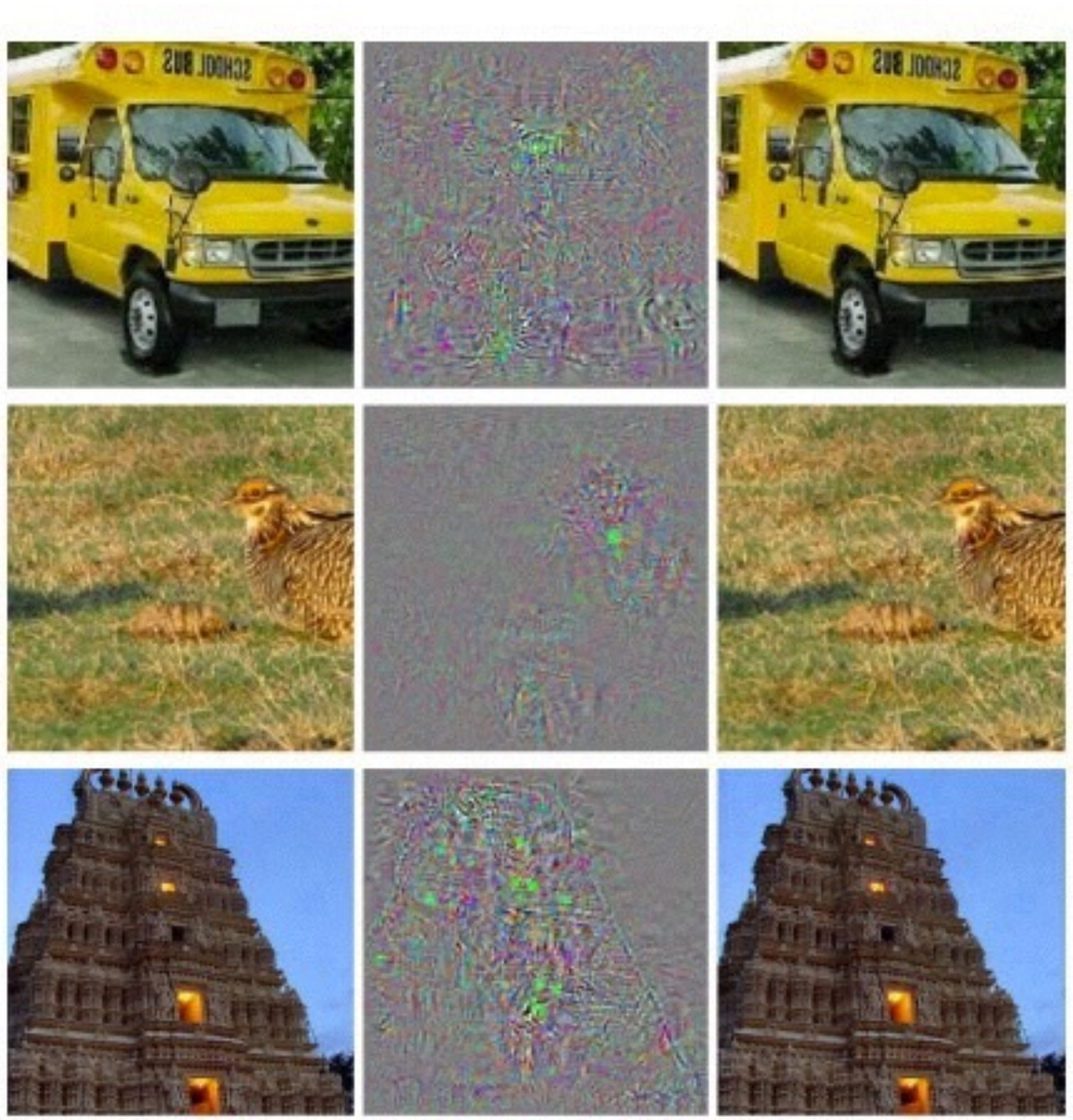
https://www.re-work.co/blog/deep-learning-peter-sadowski

Adversarial Examples



Paper: Explaining and Harnessing Adversarial Examples

Adversarial Examples



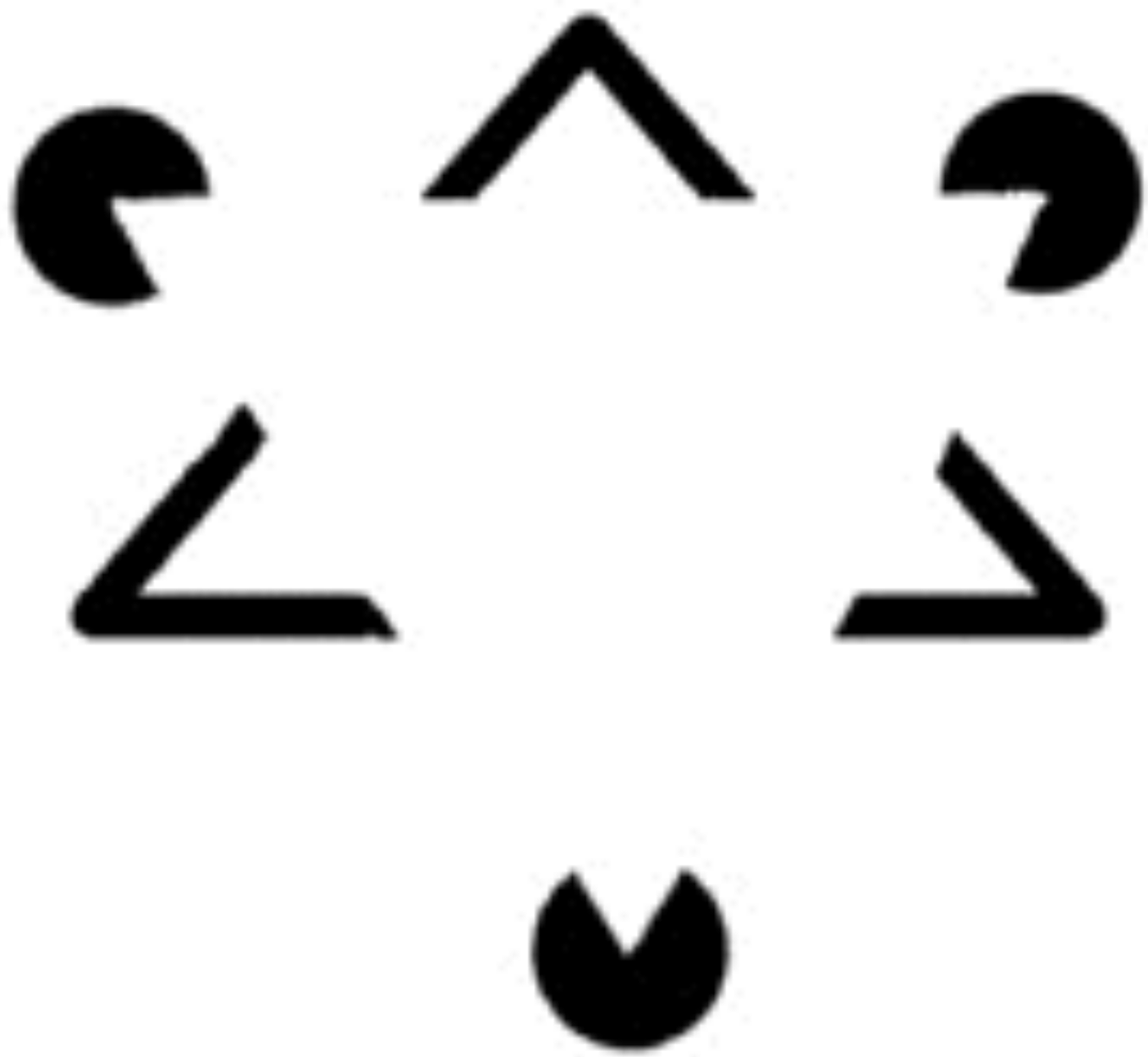
Paper: Intriguing properties of neural networks

Adversarial Examples

More training data?!

Paper: Intriguing properties of neural networks

Gestalt Law of Closure



Conclusion

Pros

- no feature engineering necessary
- setting state of the art for
  - computer vision,
  - speech recognition and
  - some text analysis
- full potential still unknown
  - they get better with more data

Cons

- doesn't work out of the box
- many choices
  - architecture
  - hyper parameter
  - learning algorithm
- needs huge amounts of data
- computational expensive

➡ lots of expensive experiments

Thank you